Smoking cessation in South Africa: cigarette prices, plain packaging, and illicit trade

Nicole Vellios

Thesis presented for the Degree of

DOCTOR OF PHILOSOPHY

in the Department of Economics

UNIVERSITY OF CAPE TOWN

14 October 2022

Supervisors: Corné van Walbeek (UCT), Hana Ross (UCT), and Emmanuel Guindon (McMaster University)

Word count: 65 920

DECLARATION

This work has not been previously submitted in whole, or in part, for the award of any degree. It is my own work. Each significant contribution and quotation in this dissertation from the work of other people has been cited and referenced.

Nicole Vellios

Date: 14 October 2022

ACKNOWLEDGEMENTS

Firstly, I thank God for giving me the opportunity, perseverance, ability, and strength to undertake and complete a PhD.

I also thank the University of Cape Town’s Research Unit on Economics of Excisable Products (REEP) for funding this research. Of REEP’s funders, special thanks are due to the International Development Research Centre (IDRC), through the Global Alliance for Chronic Diseases research programme, and the Bill and Melinda Gates Foundation, through the African Capacity Building Foundation (ACBF). Thanks are also due to Natacha Lecours from IDRC and Betina Edziwa from ACBF for their administrative support.

Many people helped me write this thesis. To my long-time mentor, employer, friend, and supervisor, Corné van Walbeek, thank you for always having an open-door policy, for your keen eye and ear, for comments that made this thesis infinitely better, and for graciously letting me disappear from my work responsibilities for the last 14 months to complete this thesis. I also appreciate the heavy doses of optimism during times we can now acknowledge as dire. Without your support I would have shelved this thesis long time ago.

To my co-supervisors, Emmanuel Guindon and Hana Ross, thank you for sharing your technical skills, knowledge, and time. Emmanuel, thank you for your incisive and helpful comments, and for your patience in explaining difficult concepts over many Skype calls. Hana, thank you for your encouragement, for providing feedback in record time, and for your intuition on when I should complete my research and when I should keep digging.

To Judith Singer and John Willett, even though I have never met you, for writing a textbook that made survival analysis understandable and interesting. To Emmanouil Mentzakis and Neil Buckley, thank you for your invaluable help with the discrete choice experiment and the auction.

Thank you to Elizabeth Baldwin for the excellent and meticulous copyedit, sparing me much embarrassment.

To Sharon de Bruyns, my work mom, thank you for eagerly helping with all things administrative, as you always do. Our research unit would be lost without you.

I could not have done this without my friends, so thank you to Jodie Posen, Claudia Colarossi-Ralphs, Janine Titley, Vanessa Darsamo, Kathy Seintis, and Karina Kinsey, whose conversations, prayers, and love enabled these pages.

I thank the Southern Africa Labour and Development Research Unit for their tireless efforts in creating five waves of the National Income Dynamics Study, which I used in two of the three papers.

I also thank all 1400 UCT students who participated in the plain packaging survey.

I am grateful to my cats, Alley, Ollie, and Jackson, who kept me company and gave me much needed comfort and entertainment.

And, finally, I am grateful to my mom, for her constant support and love, and for always encouraging me to study further.

ABSTRACT

The dangers of smoking are well-known and no longer contested. Despite this, many smokers struggle to quit smoking. The aim of this thesis is to investigate quitting behaviour in South Africa.

In the second chapter, I investigate, using survival analysis techniques, whether cigarette prices affect smokers' decision to quit smoking. The analysis was done using nationally representative data, the National Income Dynamics Study (NIDS). Self-reported information for onset age and cessation age was used to create smoking histories from 1970 to 2017. Each smoker was followed from the time they started smoking, either until they quit, or until the last interview if they did not quit. Monthly price data, sourced from government documents, was merged with NIDS data. Various model specifications were estimated to test the robustness of the results.

In the third chapter, I investigate whether the type of cigarette packaging, a matter which is currently being considered in South Africa, reduces the utility of cigarettes. Preferences were elicited using a discrete choice experiment. Data were collected in 2021 from University of Cape Town students. Both smokers and non-smokers were sampled. Intention to buy, intention to try, and perceptions of harm were investigated using conditional logit models. The attributes included packaging, price, and warnings on individual cigarettes. The design of the experiment accounted for illicit cigarettes so as to reflect current market conditions closely. The willingness to pay for cigarette packs with different attributes was also estimated using a Becker–DeGroot–Marschak auction.

Since increasing excise taxes increases the demand for low-priced, untaxed cigarettes, smokers may switch to low-priced cigarettes instead of quitting. In the fourth chapter, I investigate the illicit cigarette market using gap analysis. Gap analysis is based on a comparison of consumption estimates (from survey data) with legitimate sales (as declared to the excise tax authority). The gap between self-reported consumption (scaled up to account for under-reporting) and legitimate sales is an indication of the size of the illicit market. Self-reported consumption was estimated using two nationally representative surveys, NIDS and the All Media and Products Survey, allowing a long period (2002 to 2017) to be investigated. I also investigate the relationship between excise tax increases and illicit trade.

The results from the second chapter indicate that price is a significant determinant of smoking cessation. A 10% increase in the price of cigarettes was estimated to result in a

5.5%−8.6% increase in smoking cessation. Females are more likely to quit than males. Respondents with higher education are more likely to quit compared to those with less education.

Results from the third chapter indicate that plain packaging would be effective in reducing people’s utility for cigarettes. I found that smokers reported preferring not to buy plain packs and non-smokers preferred not to try plain packs. In terms of health risk, both smokers and non-smokers perceived plain packs to be the most risky to health.

My estimates from chapter 4 show that, between 2002 and 2009, the illicit cigarette market accounted for around 5% of the total market. Since 2009, the illicit cigarette market has increased sharply: by 2017 illicit trade accounted for 30%−35% of the total market. I found no evidence that excise tax increases were linked to an increase in illicit trade. When excise taxes were increasing rapidly, illicit trade was stable (2002−2009). On the other hand, when excise tax increases were relatively modest, illicit trade increased rapidly (2009−2017).

The results have several policy implications. South Africa should continue to increase the price of cigarettes through excise tax increases to encourage smoking cessation. If consumers are able to buy cheaper illicit cigarettes, the impact of price increases is likely to be reduced. The South African government should therefore implement measures to reduce the illicit trade in cigarettes, as outlined by the WHO’s Protocol to Eliminate Illicit Trade in Tobacco Products. The 2018 South African Control of Tobacco Products and Electronic Delivery Systems Bill, which, amongst other things, obliges tobacco manufactures to remove all branding and to include a graphic health warning, should be implemented.

Table of Contents

List of tables

List of figures

CHAPTER 1: Introduction

In 2015, there were approximately 8.5 million smokers in South Africa (South African Audience Research Foundation, 2015). Of those, 4.5 million indicated that they intended to quit in the near future (South African Audience Research Foundation, 2015). Understanding the determinants of smoking cessation may assist policymakers to formulate and implement appropriate policies to decrease smoking prevalence. Lowering smoking prevalence would decrease the substantial burden of disease caused by smoking in South Africa, which was estimated to be around 25 700 deaths among those aged 35−74 in 2016 (Boachie, Rossouw & Ross, 2021).

Measures to reduce tobacco consumption can decrease the number of avoidable deaths. Increasing excise taxes is the most effective tobacco control policy to reduce smoking prevalence (International Agency for Research on Cancer, 2011; U.S. National Cancer Institute and World Health Organization, 2016). Amongst adults, smoking prevalence is unlikely to increase because more people are starting smoking since after a certain age the probability on smoking onset is negligibly small. Smoking prevalence amongst adults is reduced when a substantial number of smokers quit smoking.

Plain packaging (where all branding is removed from the pack) is also effective (McNeill et al., 2017). The aim of plain packaging is to make tobacco products less appealing, thereby reducing the likelihood of smoking onset, and encouraging continuing smokers to quit or decrease consumption. Cigarette price increases and plain packaging may, however, be ineffective tobacco control instruments if consumers have access to illicit cigarettes.

Excise taxes and plain packaging are well-established policy instruments. In 2020, the most-sold brand of cigarettes in 55 countries had a total tax (excise taxes, import duties, value added tax (VAT), and other applicable taxes) that was equal to or greater than 70% of the retail price (World Health Organization, 2021a). The total tax burden exceeded the 50% mark in 109 countries (World Health Organization, 2021a). With a total tax burden of 53% in 2020, South Africa ranked 100th in the list of countries. As of October 2021, 134 countries or jurisdictions required pictorial health warnings on cigarette packs. In a further development, Australia was the first country to implement plain packaging in 2012. By October 2021, 21 countries or jurisdictions had also adopted plain packaging (Canadian Cancer Society, October 2021).

In addition to excise taxes and plain packaging, this thesis will investigate a new policy instrument: printing warnings directly on individual cigarettes. A warning on each cigarette is thought to prolong the effect of the health message, as it would be visible when a cigarette is taken out a pack and while the cigarette is being smoked, making warning messages more difficult to avoid. No country to date (May 2022) has implemented this policy. On 10 June 2022, the government of Canada formally proposed the introduction of written health warnings printed on individual cigarettes, cigars that have a filter, and cigarette tubes (Government of Canada: Health Canada, 10 June 2022). Printing warnings on individual cigarettes is also being considered in the UK (Action on Smoking and Health, 13 June 2021). Printing health warnings on individual cigarettes would be particularly important in countries such as South Africa, where a large proportion of smokers buy cigarettes as single sticks. (Van der Zee, Van Walbeek & Magadla, 2019)

Tobacco Control in South Africa

Prior to 1993, a single company, the Rembrandt Group, controlled the majority of the South African tobacco market (Van Walbeek, 2005). Rembrandt was an Afrikaner-owned company that received strong support from the apartheid government. Taxes on tobacco products were negligible (Van Walbeek, 2005). When apartheid ended and the transition to democracy began, the threat posed by smoking to public health became a priority for the new government. The end of apartheid also saw the opening up of South Africa's markets and borders to the rest of the world, ending a lengthy period of isolation. Following the transition, Rembrandt merged with British American Tobacco (BAT) in 1999, which meant that BAT controlled approximately 93% of the South African cigarette market (Van Walbeek, 2005).

Excise taxes

South Africa was one of the first middle-income countries to use excise tax increases to reduce smoking prevalence. In 1994, the government announced that it aimed to set the excise tax, which is levied as a specific tax, at a rate such that the total tax burden would equal 50% of the retail price (Linegar & Van Walbeek, 2018). The total tax burden is defined as the sum of the excise tax and VAT, expressed as a percentage of the retail price of the most popular brand. From 1994 to 1996, excise tax increases led to retail price increases. The 50% target was achieved in 1997 (Linegar & Van Walbeek, 2018). Since then, the only change occurred in 2004, when the government increased the total tax burden target to 52% of the retail price (Republic of South Africa, 18 February 2004).

Although the government sets the tax rate, the tobacco industry decides on the net-of-tax price. Thus both government-imposed taxes and industry pricing determine prices. Since the excise tax is a function of the retail price, the tobacco industry in South Africa effectively controlled the excise tax amount per pack of cigarettes for many years. Between 1995 and 2017, the real (inflation-adjusted) excise tax increased at an average rate of 7.2% per year (Van Walbeek, 2018). The largest tax growth occurred between 1995 and 2011, when the real excise tax increased at an average rate of 9.7% per year (Van Walbeek, 2018). Between 1995 and 2011, also, smoking prevalence decreased from 31% to 20% (South African Audience Research Foundation, 1995; South African Audience Research Foundation, 2011). Between 2011 and 2017, the real excise tax per pack of 20 cigarettes increased by an average rate of only 1% per year (Van Walbeek, 2018). During this time, smoking prevalence remained around 20% (South African Audience Research Foundation, 2011; Southern Africa Labour and Development Research Unit).

The increase in the excise tax in the 1997 to 2011 period was driven largely by the tobacco industry's pricing strategy of over-shifting excise taxes. Over-shifting a tax increase raises the retail price by more than the tax increase. Higher profit margins compensate the industry for the reduction in sales due to higher tax. After 2011, the established tobacco industry revised their pricing strategy in reaction to newcomers (who offered low-priced cigarettes) entering the market (Linegar & Van Walbeek, 2018). BAT's market share decreased from 81% in 2012 to 74% in 2016, while Gold Leaf Tobacco, a prominent local company, increased its market share from 3% in 2012 to 6% in 2016 (Euromonitor International).

The government does not have a formal strategy to counter the effect of inflation (for example indexing taxes based on inflation), but in general this is what they have done, especially for the period after 2011. For the past decade, *excise taxe*s have been increasing by the inflation rate, or by slightly more. As the *retail price* of the most popular cigarettes generally increased by less than the inflation rate, this meant that the tax burden gradually increased above the 52% target. In 2018, the total tax burden (excise and VAT) was 59% of the retail price. The tax share is becoming larger because retail prices are not increasing by the same amount as excise taxes.

The WHO has long, since at least 2010, recommended that excise tax should comprise at least 70% of the final consumer price (World Health Organization, 2010). Even earlier, Jha & Chaloupka (1999) suggested that the tax component of the price of a pack of cigarettes should be between 67% and 80% of the total retail cost. In its 2021 Technical Manual on Tobacco Tax Policy and Administration, the WHO notes that the share of tax in the retail price is not enough to ensure that excise tax increases will be successful in reducing demand (World Health Organization, 2021b). A tax share can be high while at the same time tobacco products remain affordable. In South Africa, the affordability of cigarettes (the cost of cigarettes relative to income) has remained unchanged for the past two decades (South African Reserve Bank, 2022; Van Walbeek, 2018).

Tobacco advertising and sponsorship, prohibition of smoking in all public spaces

The 1999 legislation, which was implemented in 2001, banned all tobacco advertising and sponsorship, prohibited smoking in all public and work places, and prohibited the distribution of free cigarettes (Republic of South Africa, 1999). In the Government Gazette of 21 August 2009 (Republic of South Africa, 2009), Parliament announced the commencement of two tobacco control acts that were passed in 2007 and 2008 (Republic of South Africa, 2007; Republic of South Africa, 2008). The laws banned smoking in partially enclosed public places, such as balconies, covered patios, verandas, walkways, and parking areas. It also banned smoking in cars when passengers under 12 years are present, and smoking in premises (including private homes) used for commercial childcare activities.

Cigarette packaging laws

In 1995, the government ordered the tobacco industry to print warnings on tobacco packaging and advertising material (Republic of South Africa, 1995). Manufacturers are only required to print a written health warning on cigarette packs. The eight rotating health warnings have not been updated since 1995. Heath warnings cover 20% of the front of the pack and 30% of back of the pack, and tar and nicotine contents are stated on the packet (Republic of South Africa, 1995)

South Africa’s cigarette packaging laws are outdated, both in relation to Africa and further abroad. Sixteen WHO AFRO countries in the WHO AFRO region have implemented graphic health warnings (Canadian Cancer Society, October 2021). Globally, 134 countries require graphic health warnings (Canadian Cancer Society, October 2021).

Plain packaging is proposed for South Africa in the 2018 Control of Tobacco Products and Electronic Delivery Systems (CTPENDS) bill (Republic of South Africa: Department of Health, 9 May 2018). If plain packaging is implemented, South Africa will be the first country to move directly from written health warnings to plain packaging with graphic health warnings (i.e., no middle step of branded packs with graphic health warnings).

All cigarettes are meant to be sold in packaging: ‘*No person shall sell or import for subsequent sale any prescribed tobacco product, unless—(a) such product is in a package*’ (Republic of South Africa, 1999). Although legislation exists that bans the sales of single cigarettes, the ban is not enforced.

Illicit trade

South Africa now has one of the highest rates of illicit trade globally (Van der Zee, Van Walbeek & Magadla, 2019). The South African Revenue Service (SARS) has gone through phases of success and failure in addressing illicit trade. From 2005 to about 2009, SARS enforcement units shut down a number of cigarette manufacturers and traders involved in fraud, smuggling, and illicit manufacturing (Independent Online, 29 June 2005; Sole, 28 October 2018). Although SARS was making progress in removing illicit cigarette manufacturers, this ended in September 2014 when Tom Moyane was appointed as SARS Commissioner. Many senior executives were removed, including personnel who worked on tax and customs enforcement and investigations (Du Toit, 26 June 2018; Kahn, 26 May 2018).

In recent years, the COVID-19 lockdown tobacco sales ban, which occurred between 27 March and 17 August 2020, exacerbated the illicit trade market. BAT, Philip Morris International (PMI), and Japan Tobacco International (JTI) lost substantial market share to smaller manufacturers during the sales ban (Filby, van der Zee & van Walbeek, 2021). Before the lockdown, 75% of respondents in a sample of 23 361 people smoked brands produced by BAT, PMI, and JTI, which decreased to 17% when the survey was conducted in June 2020 (Filby, van der Zee & van Walbeek, 2021). During the almost five-month sales ban, manufacturers and retailers produced and sold cigarettes illicitly, providing the opportunity to develop new and creative illicit distribution channels (Filby, van der Zee & van Walbeek, 2021). By September 2020, the market share of BAT, PMI, and JTI had recovered, but not fully, to 66% (Van Walbeek, Van der Zee & Filby, 10 December 2020).

Control of Tobacco Products and Electronic Delivery Systems (CTPENDS) bill

On 9 May 2018, the then Minister of Health, Dr Aaron Motsoaledi, invited the public to comment of the draft CTPENDS bill. The consultation period ended 9 August 2018. In this draft bill, the ministry of health proposes to: (1) regulate the sale and advertising of tobacco products and electronic delivery systems, (2) regulate the packaging and appearance of tobacco products and electronic delivery systems and to make provision for the standardisation of their packaging, (3) provide for standards in respect of the manufacturing and export of tobacco products and electronic delivery systems, (4) prohibit the sale of tobacco products and electronic delivery systems to and by persons under the age of 18 years, (5) prohibit the free distribution of tobacco products and electronic delivery systems, and (6) prohibit the sale of tobacco products and electronic delivery systems by means of vending machines.

Although this bill is more than four years old, it has not yet gone through the legislative process to become law. The delays are due to South Africa’s long and convoluted legislative process, industry interference, Covid-19, lack of capacity, and leadership instability (in the past four years, there have been four different ministers, including an acting minister).

World Health Organization's Framework Convention on Tobacco Control

The FCTC, which came into effect on 27 February 2005, is the world's first public health treaty (Roemer, Taylor & Lariviere, 2005). The treaty currently (April 2022) consists of 182 parties (United Nations Treaty Collection, 2022b). Although South Africa ratified the treaty on the 19th of April 2005 (United Nations Treaty Collection, 2022b), little progress has been made. The FCTC was developed with the objective of protecting people from the harmful effects of tobacco use and exposure to tobacco smoke (World Health Organization, 2003). The FCTC recommends that ratifying countries adopt policies to reduce both the demand for (Articles 6–14), and supply of (Articles 15–17) tobacco products (World Health Organization, 2003).

This thesis considers several FCTC articles, namely:

- Article 6: Price and tax measures to reduce the demand for tobacco – chapters 2, 3 and 4
- Article 11: Packaging and labelling of tobacco products − chapters 2 and 3
- Article 13: Tobacco advertising, promotion, and sponsorship – chapter 2
- Article 15: Illicit trade in tobacco products – chapters 2, 3, and 4

To assist parties to implement these articles, the FCTC's Conference of the Parties has adopted eight guidelines to date (May 2022). These guidelines cover the provisions of nine FCTC articles, specifically Articles 5.3, 6, and 8−14 (World Health Organization, 2022). Three of these guidelines are relevant to the current thesis: Articles 6, 11, and 13. In addition, the Protocol to Eliminate Illicit Trade in Tobacco Products has been developed to assist countries to reduce illicit trade (World Health Organization, 2013).

Article 6 (Price and tax measures to reduce demand for tobacco) commits parties to adopt tax and price policies that will reduce tobacco use. The Article 6 guidelines recommend that: (1) parties implement simple tobacco taxation systems by adopting specific or mixed excise systems (as opposed to purely ad valorem systems), (2) adjust tax rates regularly to account for inflation and income growth, (3) apply tax rates uniformly to all products, and (4) earmark a proportion of tobacco tax revenues to finance tobacco control (World Health Organization, 2014).

The Article 11 (Packaging and labelling of tobacco products) guidelines propose adopting measures to restrict or prohibit the use of logos, colours, brand images or promotional information on packaging other than brand and product names displayed in a standard colour and font style (plain packaging) (World Health Organization, 2008a). Article 11 guidelines also recommend health warnings on individual sticks: 'Parties should consider introducing other innovative measures regarding location, including, but not limited to, requiring health warnings and messages to be printed on the filter overwrap portion of cigarettes' (World Health Organization, 2008a).

Article 13 (Tobacco advertising, promotion, and sponsorship) guidelines, which touch briefly on plain packaging, recommend that Parties 'consider adopting plain packaging requirements to eliminate the effects of advertising or promotion on packaging. Packaging, individual cigarettes or other tobacco products should carry no advertising or promotion, including design features that make products attractive' (World Health Organization, 2008b).

The number of countries requiring plain packaging is expected to increase further, given the World Trade Organization's (WTO) ruling that Australia's plain packaging requirements are consistent with the WTO's international trade agreements (World Trade Organization, 9 June 2020). The tobacco industry had opposed plain packaging by arguing that the measure infringed WTO trade agreements, but that argument can no longer be used.

Lastly, the Protocol to Eliminate Illicit Trade in Tobacco Products outlines measures that countries should adopt to address illicit trade, for example a track-and-trace system that monitors the production and supply chain of cigarettes. The protocol states that a monitoring system should be independent of the tobacco industry to be credible. There are currently (April 2022) 64 parties to the protocol, 20 of which are in Africa (United Nations Treaty Collection, 2022a). Although South Africa signed the treaty on 10 January 2013, it has not yet ratified the protocol to become a party (United Nations Treaty Collection, 2022a).

Population group classifications in South Africa

The population group classifications used in this thesis are based on self-reporting according to Apartheid-era groups. The population group classifications used are 'African', 'Coloured', 'White', and 'Asian'. 'African' refers to black Africans. 'Coloureds', a non-derogatory term in South Africa, refers to people of mixed Khoisan, Malay, European and black African ancestry. 'Whites' refers to Caucasians, and Asians refers to those of Asian ancestry. Although apartheid ended in South Africa in 1994, these population group classifications remain the norm. In South Africa, population group embodies more than skin colour, including relative privilege, culture, and socioeconomic conditions. Despite transformation attempts by the government and private institutions, South Africa remains a racialised country.

Thesis structure

In chapter 2, I conducted a review of smoking cessation papers that used survival analysis techniques. Applying survival analysis techniques to a nationally representative dataset, I estimated the determinants of smoking cessation from 1970 to 2017. I do not consider the determinants of smoking onset as this has already been done (Vellios & Van Walbeek, 2016). I analysed how smokers responded to cigarette price changes during periods of substantial increases and periods when prices were relatively flat. Following people retrospectively over time, I matched price data to each month to see if smokers responded to price changes. Other variables, such as sex, population group, changes in tobacco tax laws, education, and income were included in the analysis.

To test whether or not plain packaging would encourage smokers to quit smoking, I conducted a discrete choice experiment in chapter 3. Discrete choice experiments are increasingly used in tobacco research (Regmi et al., 2018), as they allow policy instruments to be assessed before their implementation. Data were collected in 2021 from registered University of Cape Town students. Smokers were asked about their intention to buy, while non-smokers were asked about their intention to try. Both smokers and non-smokers were asked about perceptions of product harm. The attributes tested were packaging, price, and warnings on individual cigarettes.

In Chapter 4 I investigate the size of the illicit trade in South Africa from 2002 to 2017 using two nationally representative datasets, and data from government sources. I also investigate whether changes in illicit trade can be linked to efforts by SARS to reduce illicit trade, or to the management crisis at SARS between 2014 and 2018. Parts of this chapter have been published in *Tobacco Control* (Vellios, Ross & van Walbeek, 2019).

Chapter 5, the concluding chapter, presents the main policy recommendations.

CHAPTER 2: Determinants of smoking cessation in South Africa using survival analysis: 1970−2017

INTRODUCTION

In this chapter, I investigated whether the price of cigarettes, sex, education, income, religion, and the 1993 and 1999 tobacco control legislation were associated with smokers' decisions to quit.

Cigarette prices increased substantially between 1994 and 2010. The 1993 and 1999 laws came into effect in 1995 and 2001 respectively (Van Walbeek, 2005). In 1995 the government ordered the tobacco industry to print warnings on tobacco packaging and advertising material. The 2001 legislation banned all tobacco advertising and sponsorship, prohibited smoking in all public and work places, and prohibited the distribution of free cigarettes (Republic of South Africa, 1999).

To investigate the determinants of smoking cessation, I used survival analysis techniques. The smoking histories of ever-smokers (current smokers and ex-smokers) were re-created so that their smoking behaviour could be tracked over time. I first provide a brief overview of survival analysis and its related terms, and then present the current relevant literature. Survival analysis is discussed in detail in the methods and results section, with application to smoking cessation in South Africa from 1970 to 2017. This is the first study to investigate smoking cessation in South Africa using a survival analysis approach.

SURVIVAL ANALYSIS

Survival analysis is also known as duration analysis, event history analysis, reliability analysis, and failure time analysis. Survival models measure the probability of transition between states that do not overlap, and cover all possible states (Douglas, 1998). In this study, the two possible states are whether ever-smokers quit or not.

Combining respondents' age at the time of survey with retrospective information on smoking status allows the construction of a 'quasi-panel' dataset from cross-sectional data. This transformation is illustrated using two individuals, x and y (Table 2.1). Each respondent has several rows of data, which track individuals over the duration of their smoking habit.

The 'beginning of time' is a moment when everyone in the population occupies only one of the possible states. The distance from the 'beginning of time' until event occurrence is referred to as the 'event time' (Singer and Willett, 2003:311, 312). The beginning of time in the current analysis is defined as the age when the respondent started smoking. While some variables (e.g., race and sex) are constant over time, other variables are not (e.g., price and tobacco control policies). Person *x* started smoking in 1978 at age 15 and quit in 1985 at age 22. A separate observational record is created for each year that person *x* is known to be at risk of quitting. Although person *x* was aged 44 in 2017, once he quits smoking at age 22 in 1985, he drops out of the risk set. Person *y* started smoking in 2012 at age 23 and was still a smoker in 2017.

Table 2.1: Person-period data for two individuals

Person ID	**Year**	**Age**	**Period (t)**	**Event (quit)**	**Sex**	**Price in Rands (2016 prices)**
x	1978	15	1	0	M	13.07
x	1979	16	2	0	M	12.25
x	1980	17	3	0	M	11.22
x	1981	18	4	0	M	10.54
x	1982	19	5	0	M	10.75
x	1983	20	6	0	M	10.18
x	1984	21	7	0	M	10.22
x	1985	22	8	1	M	10.00
y	2012	23	1	0	F	29.43
y	2013	24	2	0	F	29.74
y	2014	25	3	0	F	30.05
y	2015	26	4	0	F	30.36
y	2016	27	5	0	F	29.82
y	2017	28	6	0	F	29.68

Survival analysis has many technical terms: censoring, parametric; semi-parametric; non-parametric models, hazard rate, survival rate, and continuous and discrete time. These terms are explained below in the context of smoking cessation.

Censoring

Censoring, which is common in many survival models, occurs when survival times are unknown for a subset of the study group (Singer & Willett, 2003). A censored observation is defined as an observation with incomplete information. Censoring can be right or left. Right censoring occurs when a person does not quit smoking before the study ends, as is the case with person *y* (Table 2.1). She started smoking in 2012 at age 23 and was still a smoker in 2017 when the data were collected. At the time of data collection, it is not clear whether and when person *y* will quit smoking. Right censoring can also occur if respondents are lost to follow-up during a study period, or if respondents withdraw from a study (Singer & Willett, 2003). Some individuals will never quit smoking, while others will quit, but not during the study's data collection; all these individuals are right-censored.

Right-censored observations are still included in the analysis, since excluding them would distort the distribution of event duration (Singer & Willett, 1993). Censoring makes standard statistical tools inappropriate even for simple analyses of event occurrence data. A censored event time provides only partial information, in that an individual did not yet experience the target event. Traditional statistical methods do not provide a way to analyse observed and censored event times simultaneously, while survival methods do (Singer and Willett, 2003).

Most survival data are right censored, but data can also be left censored, which occurs when a state is observed, but it is unknown when it began (Clark et al, 2003: 232). For example, a person infected with HIV, who does not know the date of first exposure, would be left censored. Unlike right censoring, which exists regardless of design, left censoring can be eliminated altogether if the 'beginning of time' is defined as the moment when all individuals in the population are at risk of experiencing the event, but none have yet done so (Singer and Willett, 2003). In the current analysis, the age that smokers started smoking is known. However, given price data limitations (no price data prior to 1970), it is not possible to match price data to smoking histories prior to 1970.

Censoring can be non-informative or informative. In an alcohol relapse study, an individual who is censored because he has moved cities is non-informative. On the other hand, censoring would be informative if he dropped out of the study because he started drinking again and stopped notifying investigators of his whereabouts. If censoring is informative, the hazard rate would be biased. The validity of survival analysis rests on the assumption that censoring is non-informative (Singer and Willett, 2003).

For the dataset used in this analysis – the National Income Dynamics Study (NIDS) – age at interview dictates censoring. Younger respondents have a higher probability of being censored because they have not had time to quit. For example, a smoker who is aged 16 at the time of interview has not had time to quit smoking. A smoker aged 65 at the time of interview has had many years to quit (assuming he started smoking at a young age).

Hazard and survival functions

Two related probabilities, hazard and survival, are used to describe and model survival data. The hazard probability refers to the proportion of the risk set (ever-smokers eligible to quit smoking in that period) who quit smoking during a given time period (Singer & Willett, 1993):

$$\hat{h}\left(t_j\right) = \frac{n\ events_j}{n\ at\ risk_j}$$

where *n events*$_j$ represents the number of ever-smokers who quit in time period *j*, and *n at risk*$_j$ represents the number of ever-smokers at risk of quitting during time period *j*. Event occurrence is conditional – an individual can quit in time period *j* only if he or she did not quit in any of the time periods prior to *j* (Singer & Willett, 1993). The trend over time is referred to as 'duration dependency' (Douglas, 1998).

The survival function refers to the proportion of the initial population that continues smoking through each successive time period (Singer & Willett, 1993). Formally, the estimated survivor probability for period *j* is the estimated survival probability for the previous period multiplied by one minus the estimated hazard probability for that period:

$$\widehat{S}\left(t_j\right) = \hat{S}\left(t_{j-1}\right)\left[1 - \hat{h}\left(t_j\right)\right]$$

The estimated survivor function provides maximum likelihood estimates of the probability that a randomly selected individual from the population will 'survive' (i.e., does not quit smoking) through each successive time period (Singer & Willett, 2003).

Continuous versus discrete time

Survival analysis models can be specified in continuous or discrete time. Continuous time methods assume that the precise time of the event occurrence is measured. Researchers in medicine and engineering can usually record event occurrence precisely. For example, epidemiologists can measure human lifetime in days using birth and death certificates, while industrial product engineers can measure a machine's lifetime in minutes or seconds.

With duration of smoking, recorded data at interview are usually grouped into age intervals (discrete units) (e.g., age of onset and age of quitting), even though starting and quitting take place in continuous time. People can start or quit smoking any day of the year, yet the observations are summarised discretely.

Econometric models using continuous time include exponential, Weibull, log-logistic, lognormal, Gompertz, and Generalised Gamma distributions (Table 2.2) (Jenkins, 18 July 2005). The shape of the baseline hazard informs the choice of model. For example, a Weibull model can only be used for monotonically increasing, decreasing, or constant shapes of the hazard function. A Weibull model therefore should not be used if the hazards of quitting decrease in the first few years of being a smoker, and then increase in later years.

Table 2.2: Examples of functional forms for the hazard rate

Continuous time ***Parametric***	**Continuous time** ***Semi-parametric***	**Discrete time** ***Non-parametric***
Exponential	Piece-wise constant exponential	Logistic
Weibull	Cox proportional hazards model	Complementary log-log
Log-logistic		Probit
Lognormal		Linear probability model
Gompertz		
Generalised Gamma		

Source: Adapted from Jenkins, S.P. 18 July 2005. Survival analysis. Unpublished manuscript, Institute for Social and Economic Research: University of Essex.

Duration dependency is also referred to as *time* or *time at risk* or *functional form*. Continuous time models are designed to deal with continuous duration times; duration dependency does not need to be specified (Hess & Persson, 2012). For example, a Weibull model uses a Weibull distribution to model duration dependency. Similarly, the Cox proportional hazards model is estimated without having to specify a functional form for the baseline hazard.

Duration dependency needs to be additionally specified in discrete hazard models (logistic, complementary log-log, probit, linear probability model). This is done by creating dummy variables corresponding to each interval, or a polynomial for time at risk. If discrete time models are estimated without accounting for duration dependency, the model resembles an exponential model (i.e., the hazard probability is flat with respect to time).

Non-parametric models (using dummy variables to account for duration dependency)

Non-parametric models make some or no assumptions about the distribution of the hazard, allowing the data to speak for themsleves (Allison, 1984). Duration dependency is accounted for by including time dummies in the equation. For example:

$$logit\ h(t_j) = [a_1D_1 + a_2D_2 + a_3D_3 + \ldots + a_kD_k] + \beta_1\boldsymbol{X}$$

where the dependent variable is the event indicator (whether or not the respondent quit smoking in that time period), each *D* represents a time period, *k* is the number of time periods under observation, and ***X*** is a matrix of variables. As a group, the *a*s represent the maximum likelihood estimates of the baseline hazard model.

Semi-parametric models: Cox proportional hazard model

The Cox proportional hazard has a specific functional form, but the exact form of the distribution of event times is not pre-determined (Allison, 1984). The Cox proportional hazards regression model (Cox, 1972) asserts that the hazard rate for the *j*th subject is:

$$h(t|\mathbf{x}_j) = h_0(t)\exp(\mathbf{x}_j\mathbf{b}) = h_0(t)\exp(b_1x_{1j} + b_2x_{2j} + \ldots + b_kx_{kj})$$

where $h_0(t)$ is the baseline hazard, $\exp(\mathbf{x}_j\mathbf{b})$ is the relative hazard, and $\mathbf{b} = (b_1, b_2, \ldots, b_k)$ is the set of coefficients on the independent variables to be estimated (Stata Netcourse 631, 2019). The Cox proportional hazards model has no intercept because the intercept in subsumed in the baseline hazard.

The baseline hazard can be increasing, decreasing, increasing and then decreasing, decreasing and then increasing, or constant. However, the shape of the hazard is the same for everyone; one person's hazard is the same as the next person's (Stata Netcourse 631, 2019). Stata's `stcox` command fits Cox proportional hazards models (after providing Stata with information on how the data are structured using the `stset` command).

To understand the Cox proportional hazards model, consider the following question: does wearing a protective hip brace (variable 'protect') reduce hip fractures? (Stata Netcourse 631, 2019). Some participants were given a hip brace, while others were not ('protect'=0 if no brace, 'protect'=1 if brace is used). The dependent variable is 'fracture' (0=no, 1=yes), while the independent variable is 'protect'. After running the regression `stcox protect, nohr` (the `nohr` option displays coefficients rather than hazard ratios), the coefficient on the protect variable is –2.05:

$$(t|\mathbf{x}_j) = h_0(t)\exp(-2.05 protect_j)$$

If protect=0, then the hazard is equal to the baseline hazard function:

$$h(t|\text{protect}_j = 0) = h_0(t)$$

If protect=1, then the hazard is equal to the baseline function multiplied by the exponent of the coefficient on the protect variable:

$$h(t|\text{protect}_j = 1) = h_0(t)\exp(-2.05)$$

The hazard *ratio* is:

$$\frac{h(t|\text{protect}_j = 1)}{h(t|\text{protect}_j = 0)} = \frac{\mathrm{h}_0(t)\exp(-2.05)}{\mathrm{h}_0(t)} = \exp(-2.05) = 0.13$$

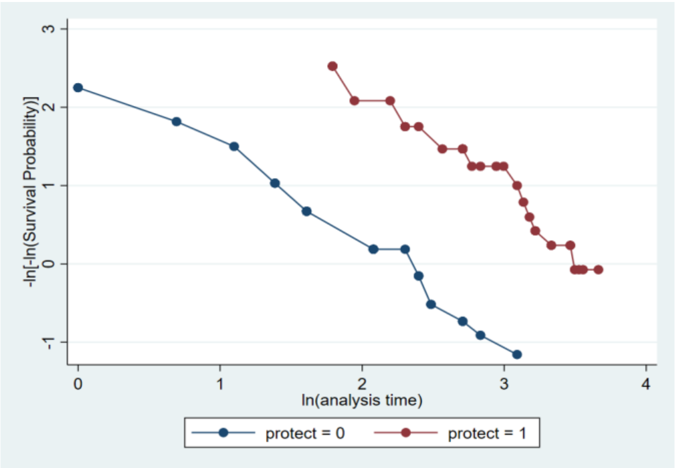
Therefore, to obtain the hazard ratio, one should exponentiate the coefficient on the variable, which is the output Stata gives in the command `stcox protect`. The shape of the hazard for those who wear the brace is the same shape of those who do not wear the brace, multiplied by a constant (0.13). At a particular time, the hazard rate for those who wear the device is exp(−2.05)=0.13 times that of those who do not wear the device. Put differently, the hazard ratio for those who wear the brace is 87% (exp $(-2.05)-1$) less than for those who do not wear the device, indicating that the hip brace is effective at preventing hip fractures.

Proportional hazards assumption

The proportional hazards assumption assumes that survival curves for different groups are roughly parallel. The hazards are considered proportional if the hazard ratio remains constant from day one of the study until the end of follow-up (Stensrud & Hernán, 2020). Using the hip fracture example, the hazard rate of those who wear the device is a multiplicative constant (0.13) of the hazard of those who do not wear the device. Because the Cox model requires the hazards in both groups to be proportional, researchers are often asked test whether hazards are proportional (Stensrud & Hernán, 2020). Stensrud & Hernán (2020) argues that statistical tests for proportional hazards are unnecessary because it is expected in almost any clinical study that the hazard ratio will vary over the follow-up period. Instead, Stensrud & Hernán (2020) reason that a hazard ratio needs to be interpreted as a weighted average of the true hazard ratios over the entire follow-up period.

Graphical methods to test the proportional hazards assumption have been developed in Stata. For discrete covariates, the command `stphplot` plots an estimate of $-\ln[-ln\{S(t)\}]$ versus $\ln(t)$ for each level of the covariate, where $S(t)$ is the Kaplan Meier survivor function (Stata Netcourse 631, 2019). Using the same example as before, `stphplot, by protect`, shows that the curves are roughly parallel (Figure 2.1), indicating that the proportional hazards assumption is valid. If the assumption is invalid, parameter estimates of the elasticities will be inconsistent.

Figure 2.1: Graph showing valid proportion hazards assumption

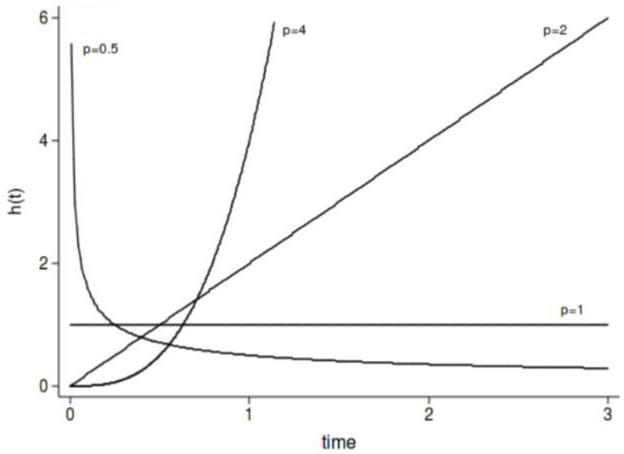


Source: Stata Netcourse 631. 2019. Introduction to Survival Analysis Using Stata. Lesson 4: page 36. https://www.stata.com/netcourse/intro-survival-analysis-nc631/.

Parametric models

Parametric models explicitly specify the distribution of the hazard. Parametric models assume that the time until an event occurs, or the time between events, comes from specific distributional forms. Parametric model are used when theory is strong on the distributional form of the hazard. The Weibull model provides monotonically increasing, decreasing, or constant shapes of the hazard function, the shape of which is determined by the estimated parameter *p* (Figure 2.2). When *p*=1, the hazard is constant, and the Weibull model reduces to the exponential model (Stata Netcourse 631, 2019). For other values of *p*, the Weibull model is not constant. The Weibull model is therefore suitable for modelling data with monotone hazard rates that either increase or decrease over time (Stata Netcourse 631, 2019).

Figure 2.2: Weibull function



Source: Stata Netcourse 631. 2019. Lesson 5 page 16. Introduction to Survival Analysis Using Stata. https://www.stata.com/netcourse/intro-survival-analysis-nc631/.

The Weibull model assumes:

$$h(t|\mathbf{x}_j) = h_0(t)\exp(\mathbf{x}_j\mathbf{b}) \text{ …..(1)}$$

$$\text{where } h_0(t) = pt^{p-1}\exp(a)\text{…..(2)}$$

where *p* is the estimated parameter, *t* is time, and *a* is a constant. Substituting equation 2 into equation 1:

$$h(t|\mathbf{x}_j) = pt^{p-1}\exp(a)\exp(\mathbf{x}_j\mathbf{b}) = pt^{p-1}\exp(a + \mathbf{x}_j\mathbf{b})$$

In the Weibull model *a*, *p*, and **b** are estimated. Using the same example as before, the Stata command is `streg protect, distribution (Weibull) nohr`. Stata provides the value for parameter *p* in the regression output. If protect = 0:

$$h(t|\text{protect}_j = 0) = 1.56t^{1.56-1}\exp(-3.59) = 0.0431t^{0.56}$$

If protect=1:

$$h(t|\text{protect}_j = 1) = 1.56t^{1.56-1}\exp(-3.59 - 2.01) = 0.0057t^{0.56}$$

Note that the coefficient on the protect variable is −2.01, which is very similar to the coefficient obtained using the Cox regression model (−2.05). Similarly, the hazard *ratio* is:

$$\frac{h(t|\text{protect}_j = 1)}{h(t|\text{protect}_j = 0)} = \frac{0.0057t^{0.56}}{0.0431t^{0.56}} = 0.13$$

The Weibull model can be specified as a proportional hazards model or an accelerated failure time (AFT) model (StataCorp). AFT models (e.g. Weibull/generalised gamma) are more appropriate when group differences are seen over a short time frame (Kay & Kinnersley, 2002). For example, it can be used when analysing the time it takes for influenza symptoms to subside, where one group is given medication, and the other a placebo. If the effects of treatment are to accelerate (or delay) the event of interest rather than having a longer-term impact, the AFT model should replace the proportional hazards model. Given that no variables in the current study have short-term effects, the AFT model is not used.

LITERATURE REVIEW

Survival analysis dates back to the 17th century. The first life table was produced in 1662 (Camilleri, 2019). Until recently, survival analysis has only been linked to the investigation of mortality rates. In the last few decades, survival analysis has extended beyond biomedical research to other fields, such as criminology, engineering, sociology, marketing, institutional research, and health insurance practice (Camilleri, 2019). The contributions of Kaplan and Meier in 1958 to estimating survival probabilities and hazard rates led to ground-breaking improvements (Camilleri, 2019; Kaplan & Meier, 1958). The proportional hazard model proposed by Cox (1972) was another significant contribution. In 1994, the first paper that estimated the determinants of smoking onset using survival analysis was published (Douglas & Hariharan, 1994). In 1998, the determinants of smoking onset and cessation using survival analysis was published (Douglas, 1998). Both these papers used US data.

An extensive methodological review has been done for smoking onset (Guindon, 2014), but not for cessation. In 2011, the International Agency for Research on Cancer (IARC) published a report titled ‘Effectiveness of Tax and Price Policies for Tobacco Control’ (International Agency for Research on Cancer, 2011). In chapter 5 (pages 183−188) of the 366-page report, the authors wrote a section titled ‘Systematic review of the scientific literature:

Impact of price on adult cessation'. The authors identified eight studies that examined the impact of prices or taxes on smoking cessation.

The IARC report provides eighteen concluding statements, which are all rated on a five-point scale from 'Sufficient evidence' (highest) to 'evidence of no effect' (lowest). One of the statements related to chapter 5, rated as 'sufficient evidence', is 'Increases in tobacco excise taxes that increase prices induce current tobacco users to quit'. 'Sufficient evidence' is assigned when 'An association has been observed between the intervention under consideration and a given effect in studies in which chance, bias and confounding can be ruled out with reasonable confidence. The association is highly likely to be causal.' Contrary to the IARC report, I did not find that the evidence was 'sufficient' as the results from the various studies on the effect of tax/price on the decision to quit smoking were mixed (as will be shown).

Only one study (Laxminarayan & Deolalikar, 2004) was conducted using data from LMICs (survival analysis not used). The rest were all conducted using data from HICs. Of the eight papers reviewed in the IARC report, four used survival analysis techniques (Douglas, 1998; Forster & Jones, 2001; López Nicolás, 2002; Peretti-Watel, 2004). The IARC handbook has several flaws: it does not cover all the literature, there is a lack of attention to effect sizes, and statistical significance is not reported in the summary table. For example, in IARC's summary of Douglas (1998), the reader assumes that the elasticity for current prices is significant, which it is not (only the coefficient on future prices is significant) (Douglas, 1998) (International Agency for Research on Cancer, 2011: 184).

The focus of this literature review is on smoking cessation papers that use survival models. I searched the computerised bibliographic databases Web of Science, MEDLINE, EconLit, and Google Scholar. Searches were last conducted on 8 October 2021.

The following search strategy was employed on all platforms: 'quit AND "duration analysis" AND price', 'quit AND "duration analysis" AND tax', 'quit AND "survival analysis" AND price', 'quit AND "survival analysis" AND tax', 'cessation AND "duration analysis" AND price', 'cessation AND "duration analysis" AND tax', 'life-course smoking', 'hazards and quitting', 'duration AND "smoking habit"', 'determinants of smoking cessation', and '"discrete-time hazard" AND "smoking cessation"'.

The selection of papers is based on the following inclusion criteria: (1) published in a peer-reviewed journal, (2) published in English, (3) includes price/tax as a covariate, (4) uses survival analysis, and (5) censoring is non-informative. Additionally, I searched NBER working papers because, although not peer-reviewed, they present early research conducted by leading economists.

In addition to the four papers in the IARC report, I identified an additional six papers published prior to 2011 (Farnworth, 2006; Kenkel, Lillard & Liu, 2009; Kidd & Hopkins, 2004; Madden, 2007; Tauras, 1999; Tauras & Chaloupka, 1999). I also identified an additional four studies published after 2011 (Gonzalez-Rozada & Montamat, 2019; Kostova, Chaloupka & Shang, 2015; Kostova, Husain & Chaloupka, 2017; Ross et al., 2014).

Of the 14 papers included in this review, three used data from the US (Douglas, 1998; Tauras, 1999; Tauras & Chaloupka, 1999), and two used data from China (Kenkel, Lillard & Liu, 2009; Kostova, Husain & Chaloupka, 2017). Others used data from Argentina (Gonzalez-Rozada & Montamat, 2019), Australia (Kidd & Hopkins, 2004), Canada (Farnworth, 2006), France (Peretti-Watel, 2004), Ireland (Madden, 2007), Poland, Russia, and Ukraine (Ross et al., 2014), Spain (López Nicolás, 2002), the UK (Forster & Jones, 2001). Fourteen low- and middle-income countries were also studied: six low- and lower-middle income countries (Bangladesh, Egypt, India, Philippines, Ukraine, Vietnam) and eight upper-middle income countries (Brazil, China, Mexico, Poland, Russia, Thailand, Turkey, Uruguay) (Kostova, Chaloupka & Shang, 2015).

All 14 papers investigated the effects of tax or price on smoking cessation. Table 2.3 presents an overview of each study included in this review. Studies are presented in chronological order, based on year of publication. The following characteristics are presented: (1) Author/s, year of publication, country of analysis, and journal, (2) Title, (3) Data and methods, (4) Tests for misspecification, (5) Sensitivity analysis, and (6) Comments.

Table 2.3: Literature review summary table

Author/s (year). Country. Journal	**Title**	**Data and methods**	**Testing for misspecification**	**Sensitivity analyses**	**Results**	**Comments**
Gonzalez-Rozada & Montamat (2019). Argentina. *International Journal of Environmental Research and Public Health*	How Raising Tobacco Prices Affects the Decision to Start and Quit Smoking: Evidence from Argentina	−Global Adult Tobacco Survey (GATS), Argentina, 2012 −Total sample (smokers and quitters): 762, of which 178 are quitters −Split-population duration model (probability of quitting: probit; time/duration dependency: Generalised Gamma) −Time-variant variables: Ln(price), length of smoking spell −Time-invariant variables: sex, region, education, birth year −Prices vary over time only −Since information in the survey is in annual terms, the authors randomly assigned a quit month within the reported year of quitting	None reported	Results presented for males and females combined, and separately.	No evidence that prices were associated with the duration of the smoking habit.	
Kostova, Husain & Chaloupka (2017). China. *Tobacco Control*	Effect of cigarette prices on smoking initiation and cessation in China: A duration analysis	−GATS, China, 2010 −Total sample (smokers and quitters): 4449 (men only), of which 698 are quitters −Split-population duration models (probability of quitting: logit; time/duration dependency: t indicates length of smoking spell defined as number of years since onset) −Time-variant covariates: price, t indicates length of smoking spell defined as number of years since onset, interaction terms between region dummy variables and a linear time trend −Time-invariant covariates: age, urban, education, wealth, region −Age is also included in regressions (unclear if age is time variant or time-invariant) −Prices vary over time and space	None reported	Regression results reported for two samples: 1). All 6 regions included in model (prices for 2 regions imputed), and 2). 4 regions where price data are available.	Results reported as marginal effects. Only split model for onset and cessation was modelled. Prices were found to reduce smoking onset, but no evidence was found that prices were associated with smoking cessation. Coefficients on urban residence and education were statistically insignificant. Coefficients on some of the wealth categories were significant, some were not. Authors did not discuss results of any coefficients (except price).	Unclear whether age (time invariant) covariate was onset age or age at interview. Also unclear why this variable was included in the model.

Author/s (year). Country. Journal	Title	Data and methods	Testing for misspecification	Sensitivity analyses	Results	Comments
Kostova, Chaloupka & Shang (2015). 16 developing countries: 6 LMICs (Bangladesh, Egypt, India, Philippines, Ukraine, Vietnam) and 8 UMICs (Brazil, China, Mexico, Poland, Russia, Thailand, Turkey, Uruguay) European Journal of Health Economics	A duration analysis of the role of cigarette prices on smoking initiation and cessation in developing countries	−GATS from 14 countries conducted between 2008 and 2010. Men and women aged 15+ −Total sample (smokers and quitters): 23 170, of which 3130 −Discrete time logit models (time/duration dependency: unclear) −Time-variant covariates: price, per capita GDP, country*calendar time −Time-invariant covariates: sex, urban, education, country, calendar year −Age is also included in regressions (unclear if time variant or time-invariant) −Prices vary over time only −Price series for most popular local cigarette brand for each country obtained from the Economist Intelligence Unit (EIU) World Cost of Living Survey −Unobserved country heterogeneity is addressed with country fixed effects and country-specific time trends −Males and females pooled. Sex specific price elasticities reported	None reported	Split-population duration models and non-split models for the pooled sample of males and females. For the analysis that splits the sample by sex, the non-split-population duration model is presented.	Results reported as marginal effects. While prices were associated with smoking behaviour in both samples, this association occurred through different mechanisms in the two samples. Higher prices were found to promote cessation in UMICs and but no evidence of this was found in LMICs. Higher education was positively associated with quitting.	In six of the countries (Bangladesh, China, Egypt, India, Thailand, and Vietnam), smoking prevalence was very low. One could argue that only males should have been considered in these countries. In fact, Kostova et al (2017), who used the same dataset in China, only considered males.

Author/s (year). Country. Journal	Title	Data and methods	Testing for misspecification	Sensitivity analyses	Results	Comments
Ross, Kostova, Stoklosa & Leon (2014). Poland, Russia and Ukraine. Nicotine & Tobacco Research	The impact of cigarette excise taxes on smoking cessation rates from 1994 to 2010 in Poland, Russia and Ukraine	−GATS, Poland & Russia: 2009, Ukraine: 2010 −Total sample (smokers and quitters): 11 106, of which 2237 are quitters −Discrete time logit models (time/duration dependency unclear) −Time-variant covariates: excise tax, country per capita income, calendar year, non-fiscal tobacco control policy index −Time-invariant covariates: sex, education, country, urban −Age also included in regressions (the paper says age is time-invariant, but this is contradicted in email correspondence with Deliana Kostova on 13 Aug 2021 where she says age is time-variant) −Taxes vary over time only −Males and females pooled	None reported	Split-population duration models and non-split models for the sample of males and females combined. For the analysis by sex, the non-split-population duration model is presented.	A 10% increase in excise tax was associated with a higher probability of smoking cessation (1.6−2.3%).	Perhaps regressions should have been done separately by country to provide individual country excise tax elasticities. It is likely that tax elasticities varied substantially by country given the difference in prices, and different quit rates. Although country fixed effects were included, the results were not reported. From 1996 to 2010, excise taxes increased from \$0.66 to \$2.46 (2010 prices) in Poland, \$0.03 to \$0.21 in Russia and \$0.03 to \$0.60) in Ukraine. Quit rates varied substantially by country: 29.9% in Poland (2009 survey), 20.4% in Ukraine (2010 survey) and 13.9% in Russia (2009 survey).

Author/s (year). Country. Journal	Title	Data and methods	Testing for misspecification	Sensitivity analyses	Results	Comments
Kenkel, Lillard & Liu (2009). China. Health Economics	An analysis of life-course smoking behavior in China	−China Health and Nutrition Survey (2000). Non-representative sample from nine provinces. Men aged 21−60 in 2000 (retrospective: 1952−2000) −Sample size of smokers and quitters unclear. Total person-years: n=217 633 −Linear probability model (duration dependency not accounted for) −Time-variant covariates: Price −Time-invariant covariates: education, age, survey year, survey year squared, wealth, occupation, urban-rural status, household size, province FE, number of years smoked −Prices vary over time only	None reported	Models estimated using alternative time trends (results not reported). Models estimated using probit model (not reported).	Small effect sizes and not statistically significant coefficients. Results sensitive to alternative time trend specifications. Results from probit model 'broadly similar' (not reported).	Authors noted that the ratio of former smokers to ever-smokers was only about 0.06 (i.e., very few quitters). The sample in descriptive stats table was not the same as the sample in the regressions. Although authors used survival analysis techniques, methods were not well explained.
Madden (2007). Ireland. Applied Economics	Tobacco taxes and starting and quitting smoking: does the effect differ by education?	−Saffron survey (1998). Cross sectional survey of Irish women −Total sample (smokers and quitters): 348, of which 102 are quitters −Generalised Gamma, Exponential, Weibull −Time-variant covariates: taxes, tax*education, time, time^2/100, time^3/1000 (the author does not explain what 'time' represents. Since time/duration dependency is embedded in the continuous time models he used, 'time' must be calendar time) −Time-invariant covariates: education, marital status, health knowledge, cohort dummy (age 33 or less) −Taxes vary over time only	Graphical assessments (Cox–Snell residuals), Log likelihood, Ramsey RESET, AIC.	Split-population model (results qualitatively similar to those of non-split model).	No evidence that prices were associated with the duration of the smoking habit. Results should be interpreted with caution as the sample was very small. For example, the author noted: 'Tax seems to be most effective in terms of encouraging quitting for those with the least education'. However, there were only nine quitters with least education.	

Author/s (year). Country. Journal	Title	Data and methods	Testing for misspecification	Sensitivity analyses	Results	Comments
Farnworth (2006). Canada. *Substance Use and Misuse*	What Motivates Daily Cigarette Smokers To Quit? Retrospective Annual Discrete Duration Analysis	−Cross-sectional Canadian National Population Health Survey (cycle 3: 1998 and 1999) −Total sample (smokers and quitters): 6300 (number of quitters not specified) −Discrete time probit model (time/duration dependency: unclear) −Time-variant variables: calendar day on which each time span ends, number of spans during which a person smoked cigarettes daily, time since interview, education, price of cigarettes, price of alcohol, and birth of a child, ln(time), ln(time^2) −Time-invariant: sex, onset age, language first learned, race, lifetime health restrictions, province −Prices vary over time only −Weights are used in the regressions −Males and females estimated separately	None reported	None reported	Females were more forward looking than males. Males who started smoking daily at a young age were unlikely to quit. Birth of a child seemed to encourage a mother and father to quit. People with post-secondary education were more likely to quit.	
Kidd & Hopkins (2004). Australia. *The Economic Record*	The hazards of starting and quitting smoking: some Australian evidence	−1990 National Health Survey (cross-section) −Total sample (smokers and quitters): 4946, of which 1830 are quitters. −Weibull and Generalised Gamma −Split-population duration model (probability of quitting: probit; time/duration dependency: Weibull) −Time-variant covariates: log(price), calendar time trend (quartic polynomial) −Time-invariant covariates: Australian born, education, sex −Prices vary over time and space −Price data are only available from 1963 onwards, which restricts sample to individuals aged up to 37 in 1990. Sample also restricted to those aged 27–37 (individuals who might reasonably be assumed to have completed their education) −Males and females pooled	LR tests to discriminate between split and non-split models and between pooled and sex-specific models.	Weibull, Generalized Gama, split-population duration models. Models split by sex, and pooled.	No evidence that prices were associated with the duration of the smoking habit. Being male significantly increased the time to quit. Higher educational attainment decreased the time to quit.	The focus of this paper was on onset. Less on cessation.

Author/s (year). Country. Journal	Title	Data and methods	Testing for misspecification	Sensitivity analyses	Results	Comments
Peretti-Watel (2004). France. International Journal of Drug Policy	Pricing policy and some other predictors of smoking behaviours: an analysis of French retrospective data	−1999 cross sectional telephone survey (French Health Barometer). Representative of the French population aged 12–75 years −Total sample (smokers and quitters): 7144, of which 2628 are quitters. −Discrete time logit model (time/duration dependency: unclear) −Time-variant covariates: age, age-squared, parenthood, price −Time-invariant covariates: sex, academic achievement, onset age (used as a proxy for potential addiction) −Prices vary over time only	None reported	To investigate if the determinants of smoking cessation vary as people age, Peretti-Watel estimates three sub-models with distinct age ranges (cessation at age 20 or before, cessation between ages 21 and 30, and cessation after age 30).	Price strongly correlated with quitting for full sample, but not for sub-sample of those who quit at age ≥20. Pregnant women, husbands/partners of pregnant women, and mothers and fathers were more likely to quit. High school graduates were more prone to quit than those who did not graduate from high school. Higher ages of smoking onset associated with lower probabilities of cessation.	From the sub-models of those who quit smoking at age 20 or younger, the author concluded that cigarette price was not a significant predictor of cessation. However, the sample size of this group was not transparently reported. If the sample was very small, the results may not be robust.
Forster & Jones (2001; 2003). Britain. Journal of the Royal Statistical Society	The role of tobacco taxes in starting and quitting smoking: duration analysis of British data	−British Health and Lifestyle Survey (1984). Representative sample of individuals aged 18+. Retrospective (1920−1984) −Total sample (smokers and quitters): 2480 males, 2482 females, of which 1176 males quit and 938 females quit −Weibull and Generalised Gamma models (preferred to Cox). Full regression results presented for continuous time Weibull and Generalised Gamma models) −Time-variant covariates: Ln(tax), year (years since 1920), year^2/100, year^3/1000, year^4/10000 −Time-invariant covariates: sex, ethnic origin, parental smoking, education, and social class −Taxes vary over time only −Split-population model for onset but not for cessation	Plots of cumulative Cox–Snell residuals. Schoenfeld residuals and Grambsch & Therneau (1994) global test to investigate Cox non-proportionality assumption. LR tests to discriminate between pooled and sex-specific models.	7 alternative models were run. Tax elasticity estimates from these regressions are presented (Table 6). E.g., Weibull model with discrete time instead of continuous time (benchmark model).	The estimated tax elasticity of the number of years of smoking before quitting was 0.60 for men (significant) and 0.46 for women (insignificant). Parental smoking was not significantly associated with quitting. Those with higher educational attainment smoked for shorter durations.	The authors used 'tax per cigarette' as a proxy for cigarette price. They wrote: 'As tobacco duty has been a high proportion of the price of cigarettes throughout the century, this may be a reasonable proxy for the price of cigarettes. However, the measure may be contaminated by variations in the share of the tax in the full price of cigarettes over time'. The authors noted that their results may be sensitive to the choice of price deflator.

Author/s (year). Country. Journal	Title	Data and methods	Testing for misspecification	Sensitivity analyses	Results	Comments
López Nicolás (2002). Spain. Health Economics	How important are tobacco prices in the propensity to start and quit smoking? An analysis of smoking histories from the Spanish National Health Survey	−Spanish National Health Survey (1995, 1997). Type: retrospective (1957–1990) −Total sample (smokers and quitters): 2305 males and 1817 females, of which 474 males quit and 395 females quit −Weibull model (preferred to Generalised Gamma and Cox models which were also investigated) −Time origin: smoking onset age −Sample restricted to individuals born after 1947, none started smoking before age 10, therefore followed from 1957 −Time variant covariates: Average price of ‘black’ cigarettes (the tobacco in ‘black’ cigarettes is darker than traditional cigarettes as less chemicals are used during the production process), trend, trend^2, trend^3, 2 dummy variables to control for tobacco control policies (1984 and 1992) −Time-invariant covariates: education, age (born pre-1967; 1967–1976; 1977+) −Prices vary over time only −Regressions estimated for males and females separately	Graphical methods (plots of the cumulative Cox–Snell residuals) did not offer a clear basis for model discrimination. Reset test, AIC, Grambsch and Therneau global test for proportional hazards assumption, and Schoenfeld residuals.	Weibull model with prices of ‘blond’ (traditional) cigarettes and weighted price index (results not robust). Weibull model with the same independent variables, plus a set of 4 dummy variables activated at 5, 10, 15, and 20 years before interview date (quitting question: 'How long ago did you stop smoking’) (heaping effect slightly underplays price effect, but sign and significance of price is robust).	Elasticity of quitting with respect to the price of black tobacco by sex: Males –1.32, Females –1.50 Younger cohorts tended to have shorter smoking durations Disparate patterns for education associations across sex: educated males had shorter smoking durations than educated females.	Black cigarettes were cheaper than blond cigarettes. Smokers of black cigarettes might be have been composed of one group of smokers with a high degree of price responsiveness. Smokers of blond cigarettes might have been less price responsive. An alternative explanation was that the whole of the population was price responsive, but smokers moved across the price/brand spectrum when prices increased.

Author/s (year). Country. Journal	Title	Data and methods	Testing for misspecification	Sensitivity analyses	Results	Comments
Tauras and Chaloupka (July 1999). USA. NBER Working paper	Determinants of smoking cessation: An analysis of young adult men and women	−Longitudinal data from US Monitoring the Future Survey (MFS) (High school seniors at first interview, tracked over time for up to fourteen years) −Smokers and quitters: 4826 females and 4752 males. Number of quitters not reported −Cox proportional hazards model −Time-variant covariates: Price, clean indoor air index, private workplace restriction, restaurant restriction, indoor restriction, work status*private workplace restriction, yearly income, age, frequency of participation in religious services, urban/rural, work hours, marital status, family structure (e.g. live alone), number of years of formal schooling, college status, average number of hours worked weekly, urban/rural, region (Northeast, South, Midwest, West), year, year^2 −Time-invariant covariates: race −Prices vary over time and space −Regressions estimated for males and females separately	None reported	4 models split by sex. First model omits clean air index a& the smoking restriction variables. Model 2 are identical to model 1, except clean indoor index is added. Model 3 identical to model 2, except clean indoor index replaced with the three indicators for smoking restriction. Model 4 identical to model 2 except clean indoor index is replaced with the interaction term (work status*private workplace restriction).	The real price of cigarettes had a positive and statistically significant association with the quitting hazard for both males and females in all the models. The price elasticity among males ranged from 1.07 to 1.17 and had an average elasticity of 1.12. Price elasticity among females ranged from 1.17 to 1.21 and had an average elasticity of 1.19.	Price elasticities seemed high, especially in comparison to Tauras (1999) who used the same dataset. Tauras (1999) considered multiple quit events whereas Tauras and Chaloupka (1999) considered only the first quit event.

Author/s (year). Country. Journal	Title	Data and methods	Testing for misspecification	Sensitivity analyses	Results	Comments
Tauras (November 1999). USA. NBER Working paper	The transition to smoking cessation: evidence from multiple failure duration analysis	−Longitudinal data from US Monitoring the Future Survey (MFS) (High school seniors at first interview, tracked over time for up to fourteen years). Sample size not specified −Stratified multiple-failure Cox regression and Gompertz −Time-variant covariates: price, three dichotomous clean indoor air indicators reflecting state level restrictions on smoking in private worksites, restaurants, and any other public places, income, type of community, marital status, family structure, mother's work status while growing up, religious participation, hours worked, formal years of schooling, college enrolment status, region, and dummy year variables to control for year fixed effects −Time-invariant covariates: race, sex, parental education −Prices vary over time and space −Males and females pooled	None reported	8 regressions for Cox and 8 for Gompertz. Second, third, and fourth regressions identical to first, except three dichotomous clean indoor air indicators are replaced by at most one clean indoor air indicator. Regressions 5-8 identical to regressions 1-4, except regressions 5-8 contain nine dichotomous region indicators to control for regional fixed effects.	Prices were significantly associated with quitting in all models estimated using the stratified Cox regression. Prices were positively associated with the quitting hazard at the 5% significance level for all the models estimated using the Gompertz model, with the exception of two regressions which were significant at the 6% level. Average elasticity was 0.35 (Cox) and 0.34 (Gompertz). Males were significantly less likely to quit smoking than females.	
Douglas (1998) USA. Economic Enquiry	The duration of the smoking habit	−US National Health Interview Survey: Cancer Risk Factor Supplement (1987) −Representative sample (excludes individuals over 12 in 1954 and those who were <25 at interview) −Total sample (smokers and quitters): 4526, of which 1421 are quitters −Weibull, split-population duration model (probability of quitting: probit; time/duration dependency: Weibull) −Time-variant covariates: prices by state (past, current & future), index of state regulations, dummy indicator to control for 1964 surgeon's general report, broadcast ban −Time invariant covariates: sex, ethnicity, education, smoking intensity, household income, T (table 1 says T is 'age started smoking', text on page 58 says 'non-smoking duration spell'), marital status −Prices vary over time and space −Males and females pooled	None reported	Results reported with and without state regulations	Current cigarette prices had an unexpected negative coefficient, but it was statistically insignificant. Future price affected smokers' decision to quit. Greater amount of lifetime education was strongly associated with higher quitting hazards. Males were more likely to quit. Family income had a small but statistically positive association with quitting hazards.	The focus of this paper was on addiction: Are smokers rational or irrational? The author was trying to solve this by including future prices in the regressions. He did the analysis on a split sample (to account for those who will never quit), and on a non-split sample. The results were near identical for cessation but not for onset. The author included smoking intensity as a proxy for addiction. However, the author noted that the variable might be endogenous and therefore suspect.

Most papers considered onset and cessation. Papers that only looked at cessation include Ross et al. (2014), Tauras (1999), Farnworth (2006), and Tauras & Chaloupka (1999). Although Kidd & Hopkins (2004) considered cessation, the section on cessation is brief compared to the section on onset.

By using retrospective data, researchers created a pseudo-panel. This allowed them to use time variations in cigarette taxes or prices to account for the impact of taxes or prices on smoking cessation. All authors included in this review reconstructed smoking histories by expanding cross-sectional surveys, except for Tauras & Chaloupka (1999) and Tauras (1999) who used longitudinal data from the US Monitoring the Future Survey (MFS).

How smoking onset and cessation were defined varied widely across studies. Little distinction was made between experimentation, occasional smoking, current smoking, or daily smoking. None of the authors provided sensitivity analyses on alternative measures of smoking onset and cessation. This has been done in two onset papers (Cawley, Markowitz & Tauras, 2004; Tauras, O'Malley & Johnston, 2001). The authors of both papers found that models with alternative measures of smoking onset have large differences in effect sizes.

All papers considered the transition to quitting as a single failure, except for Tauras (1999), who was the only author to model the dynamics of multiple quit decisions using panels from the MFS. The largest sample of ever-smokers is of 23 170 respondents from 16 countries (Kostova, Chaloupka & Shang, 2015), while the smallest sample of ever-smokers is 348 respondents in Ireland (Madden, 2007).

Papers not included in review

Marti (2014) used survival models to estimate the association between tobacco control expenditure and smoking onset and cessation in Switzerland, but he did not control for tax or price increases. A previous paper by the same author (Marti, 2010) looked at quitting relapse (i.e., the transition from quitting to relapse, not from smoking to quitting). I did not include Kostova (2013) because censoring was informative. The author used the Global Youth Tobacco Survey (GYTS) data from 48 low-, middle-, and high-income countries to explore the association between cigarette prices and smoking onset and cessation. Kostova (2013) constructed a retrospective dataset to follow individuals from the age of eight for an average of seven years. A key assumption of survival models is that censoring should be non-informative: the mechanism that causes censoring of individuals should not to be related to the probability of an event occurring (Singer & Willett, 2003). The GYTS data are problematic for onset, and even more so for cessation, as GYTS respondents have not had enough time to quit (or even to start) smoking.

Econometric models

Continuous and discrete time

Clearly explaining how duration dependency was accounted for in discrete choice models is crucial. Many papers, for example Kostova, Chaloupka & Shang (2015), who used a logit model, and Farnworth (2006), who used a probit model, did not provide sufficient detail for the reader to understand how duration dependency was accounted for.

Kenkel, Lillard & Liu (2009) did not account for duration dependency in their linear probability model (LPM). Y equals 1 if a person started or stopped smoking in a particular year and 0 otherwise. With an LPM, it is possible to get $\hat{y} < 0$ or $\hat{y} > 1$, which is nonsensical since a probability cannot be below 0 or above 1. This is a potential problem with using the LPM. A logit or probit model solves this issue as these models are specifically made for binary dependent variables and always result in $0 < \hat{y} < 1$. The authors say that broadly similar results from the probit models are available on request, so it seems, in this case, LPM and probit models gave similar results. Kenkel, Lillard & Liu (2009) include year and year squared in the regressions, as well as age in four categories (base: 14–24, 25–44, 45–59 and 60+).

Duration dependency and calendar year are not the same. Some authors include calendar year, but this is unrelated to duration dependency. For example, Forster & Jones (2001) include a variable 'year' to measure the number of years since 1920 and included a quartic polynomial in 'year' to capture any trends in the data that are independent of the tax effects. Similarly Kidd & Hopkins (2004) include a set of variables capturing time in a flexible polynomial, a quartic polynomial in the number of years since 1963 (the first calendar year of the analysis). Madden (2007), who used Generalized Gamma, exponential, and Weibull models, included a cubic function for time to allow 'for the possibility of a secular drift in smoking habits over time'.

Ross et al. (2014) used logit models (how duration dependency was accounted for is unclear). They included age as a time-variant covariate (the paper suggested time invariant, but email correspondence on 3 August 2021 with Deliana Kostova confirmed that it was time variant). The authors also included a calendar year variable to capture a common time-trend in smoking.

Tauras & Chaloupka (1999), who used a Cox model, included age, year, and year squared (all time varying). Tauras (1999) used stratified multiple-failure Cox and Gompertz models. Tauras (1999) included dummy variables to control for year fixed effects (1977−1993).

López Nicolás (2002) and Forster & Jones (2001) estimated three models: Cox, Weibull and Generalised Gamma. López Nicolás (2002) searched for the preferred specification using log likelihood values (the greatest log likelihood values are obtained from the Weibull model). Forster & Jones (2001) estimated both continuous and discrete time versions of the Weibull model.

There is a large variety of ways that duration dependency is accounted for in the existing literature. This variation in approaches can have a substantial impact on the findings.

Split-population duration models

In onset survival analysis, the assumption that all respondents will eventually start smoking is unrealistic since a substantial proportion of the population will never smoke at any stage of their lives. The decision to use a split-population duration model for smoking onset studies is therefore straightforward.

On the other hand, using split-population duration models for cessation analyses is more controversial; there is no consensus in the cessation literature. One can argue that not all smokers will eventually quit (so the model should be applied), or one can argue that all smokers will eventually quit when they die (so the model should not be applied). Some authors used split-population duration models, others used non-split models, while some used both.

Gonzalez-Rozada & Montamat (2019) used a split-population duration model. They used a probit to model the probability of quitting, and duration dependency was modelled using a Generalised Gamma distribution. Madden (2007) reported results from non-split-population models only. However, he also presented split models and noted that the results obtained were qualitatively similar to non-split models. Kidd & Hopkins (2004) used Weibull and Generalised Gamma models. They also used split-population duration models (probability of quitting: probit; duration: Weibull). The results were robust across specification.

Douglas (1998), who used a non-split and a split model for both onset and cessation, argued that was it unreasonable to use an empirical model that imposed the assumption that everyone will eventually start and quit. He argued that many people will never quit smoking while they are alive. Douglas (1998) estimated a split-population duration model (probability of smoking: probit, time/duration dependency: Weibull) and a non-split model (Weibull). The results for the two types of models for onset were different, but the results for cessation were nearly identical (Douglas, 1998).

Forster & Jones (2001) and López Nicolás (2002) used split-population duration models for onset, but not for cessation. For China, Kostova, Husain & Chaloupka (2017) used split-population duration models for onset and cessation, whereas Kenkel, Lillard & Liu (2009) used non-split models. Neither Kostova, Husain & Chaloupka (2017) nor Kenkel, Lillard & Liu (2009) compared results from split models with those of non-split models.

Kostova, Chaloupka & Shang (2015) presented split-population duration models and non-split models for the sample of males and females combined. The non-split population duration model was presented for males and females separately. Tauras & Chaloupka (1999) and Tauras (1999) used non-split models.

Madden (2007) noted: 'We do not employ the split-population model for quitting since it seems more reasonable to assume that from a population of smokers, all, or at least a majority of them, will quit or would eventually quit if they could be observed for long enough, than to assume that from a population of non-smokers, all will eventually start smoking'. Farnworth (2006), who only considers cessation, also did not use a split-population duration model.

Split by sex or pooled sample

Douglas (1998), Kidd & Hopkins (2004), and Tauras (1999) pooled males and females. Farnworth (2006), Forster & Jones (2001), López Nicolás (2002), Kostova, Chaloupka & Shang (2015), Tauras & Chaloupka (1999), and Peretti-Watel (2004) estimated separate models for males and females. Some authors, for example Forster & Jones (2001), based their decision to split the sample on the results of Likelihood Ratio tests, while others, for example Farnworth (2006) did not justify the decision to estimate separate models.

Kostova, Husain & Chaloupka (2017) and Kenkel, Lillard & Liu (2009), included only men since so few women smoked cigarettes in China. In six of the countries (Bangladesh, China, Egypt, India, Thailand, Vietnam) considered in Kostova, Chaloupka & Shang (2015), smoking prevalence among females was very low. Although smoking prevalence was not reported, the sample of male smokers in these countries was large, indicating that female smoking prevalence is low, e.g., 96% of the sample of smokers in Bangladesh are males. One could argue that only males should have been considered in these countries. In fact, Kostova et al. (2017), who also used the same dataset (GATS China) as Kostova, Chaloupka & Shang (2015), only considered males.

Madden (2007) considered females only (the focus of the survey used was on hormone replacement therapy). Gonzalez-Rozada & Montamat (2019) presented results for all individuals and by sex.

Whether or not to split the sample by sex, or to pool the sample of male and females depends on data availability, smoking rates by gender, and results from Likelihood Ratio tests.

Beginning of time

Gonzalez-Rozada & Montamat (2019), Tauras (1999), Tauras & Chaloupka (1999), Madden (2007), Kidd & Hopkins (2004), and López Nicolás (2002) started their analyses from when respondents began smoking. Starting ages therefore varied by individual. This is in contrast to onset models, where authors choose the age at which they start following individuals (e.g., age 10).

Gonzalez-Rozada & Montamat (2019) only had price data starting from January 1996. They therefore excluded all individuals older than 27 in 2012 (survey year). Similarly, López Nicolás (2002) dropped respondents who started smoking before 1957 (when price data became available). He used individuals born after 1947 and assumed they were at risk of quitting from when they started smoking. As none of the individuals started smoking before 1957, price data exist for all periods at risk.

The approach of dropping respondents with no corresponding price data differed from the approach of Kostova, Husain & Chaloupka (2017) and Ross et al. (2014). These authors did not drop these respondents, but followed them from when price data were available. This was because they did not have sufficient time series data on prices. Dropping these respondents would have decreased the sample size substantially. The approach used by López Nicolás (2002) was more precise as the beginning of time was well defined.

Ross et al. (2014) used the Global Adult Tobacco Surveys from Russia, Ukraine, and Poland. People were followed from when tax data were first available (1994 for Poland, 1995 for Russia, and 1996 for Ukraine), which was not necessarily from when they started smoking. If a person initiated after 1994/1995/1996 (when tax data were available), then the period of observation would be complete because there would be tax data to match all years of follow-up. The authors also included people who had initiated smoking prior to 1994/1995/1996. For those, the period of observation was left-truncated. This is a limitation of the paper, but the alternative (entirely dropping those individuals) was less favourable because it reduced the sample size (email correspondence with Deliana Kostova: 19 July 2021).

The same approach was adopted in Kostova, Chaloupka & Shang (2015). Although GATS allowed the authors to construct each individual’s smoking behaviour back to birth, they were limited by the length of the cigarette price series available for that person’s country of origin.

Weights

Since weights are designed for cross-sectional data, their application to a pseudo-panel may not be appropriate. The only time it might be appropriate to use weights is if a population has not changed substantially over time. For example, survey weights for the year 2020 are designed to represent a country in that particular year. Applying the same weights to the data in 1990 will be problematic if the population has grown, and if variables used to create the weights have changed (e.g., population group). Farnworth (2006) is the only author who applied survey weights to the regressions. Weights were also applied to a regression in one paper in the smoking onset literature (Guindon, Paraje & Chávez, 2018).

Price/tax

More than half of the papers (Forster & Jones, 2001; Gonzalez-Rozada & Montamat, 2019; Kenkel, Lillard & Liu, 2009; Kidd & Hopkins, 2004; López Nicolás, 2002; Madden, 2007; Peretti-Watel, 2004; Ross et al., 2014) provided figures to show how prices or excise taxes changed over time. Other authors (Douglas, 1998; Kostova, Chaloupka & Shang, 2015; Kostova, Husain & Chaloupka, 2017; Tauras, 1999; Tauras & Chaloupka, 1999) did not provide this information. This is a significant omission as the reader does not know how prices changed over time. If there is no change in price/tax, then the coefficients on price/tax are meaningless; price variation is imperative to estimate how individuals behave when prices change.

Prices/taxes can vary over time only, space (e.g., state or province) only, or over time and space. State-level prices were used in all three papers that used US data (Douglas, 1998; Tauras, 1999; Tauras & Chaloupka, 1999). Kidd & Hopkins (2004) used price data representing eight of Australia's major cities. Kostova, Husain & Chaloupka (2017) use prices for six Chinese regions.

All authors who used prices considered only one price trend, except for López Nicolás (2002) who considered three price trends: 'black cigarettes' (the tobacco in 'black' cigarettes is darker than traditional cigarettes as fewer chemicals are used during the production process), 'blond' (traditional) cigarettes, and a weighted (by sales) average price of black and blond cigarettes.

Price and tax data were obtained from a variety of sources. Douglas (1998), Tauras & Chaloupka (1999), and Tauras (1999) obtained state-level cigarette price data from the Tobacco Institute. Prices were matched to the survey on the basis of each respondent's current state of residence.

Douglas (1998), who investigated the rational addiction model of Becker & Murphy (1988), used three price levels in the regressions: past, current, and future prices. By including future prices, Douglas (1998) tested the theory that smokers were forward-looking and rational. Douglas (1998) did not specify how past and future prices were created. It is also unclear how respondents would know what future prices would be, unless there was a clear excise tax policy in place that outlined excise tax increases from year to year.

Gonzalez-Rozada & Montamat (2019) obtained price data from the National Ministry of Agriculture. Since price data were given in annual terms, the authors randomly assigned a month when individuals quit in the reported year of quitting. Madden (2007) used tax data from the Irish government agency responsible for customs, excise, and taxation. Kidd & Hopkins (2004) obtained an index of tobacco and cigarettes by regional capital city (eight cities) from the Australian Bureau of Statistics.

Forster & Jones (2001) used tax per cigarette. The authors noted that this measure may be contaminated by variations in the share of tax in the full price of cigarettes over time. In countries where over-shifting or under-shifting is uncommon, using taxes is a reasonable proxy for price, as tax is fully passed through to the retail price. If over-shifting is prevalent, as was the case in South Africa between 1994 and 2010, then using excise taxes is not advisable.

Tauras (1999) noted that when retrospective data were used, the current location may not have matched the location at the time respondents chose whether to quit or continue smoking. If the person had moved, there will be errors in matching prices to respondent's previous residential locations. All previous prices that a respondent would have paid for cigarettes were matched to the respondent's current state of residence at the time of the survey. Studies that used a price indicator measured at subnational level, e.g. state (Douglas, 1998; Tauras, 1999; Tauras & Chaloupka, 1999), region (Kostova, Husain & Chaloupka, 2017) or province (Kenkel, Lillard & Liu, 2009), and that experienced high levels of within-country migration (or that use a long time series) will be affected. In countries where there were high levels of within-country migration, mismatched prices only became a problem if there were substantial regional differences in price at any point.

Forster & Jones (2001) noted that their results may be sensitive to their choice of price deflators. Such studies typically used national price indices to deflate province-level and state-level prices. Tauras (1999), Douglas (1998), and Kenkel, Lillard & Liu (2009) deflated prices by national CPI. Kostova, Husain & Chaloupka (2017) corrected for inflation using China's gross domestic product (GDP) deflator. The GDP deflator can be misaligned with CPI. If export prices were to increase, for example, that would impact the GDP deflator, but the effect would not be felt by the inhabitants, because they do not buy the exported goods. A much better deflator to use, if one cannot use the CPI, is the Gross Domestic Expenditure deflator.

Other variables

Few authors controlled for other tobacco control variables than tax or price. López Nicolás (2002) included dummy variables to capture the effects of advertising campaigns (1984) and a ban on smoking in public transport and improvements in health warnings (1992). Tauras (1999) and Tauras & Chaloupka (1999) included indicators reflecting state-level restrictions on smoking in private worksites, restaurants, and other public places. Douglas (1998) used two dummy variables, one to account for the 1964 Surgeon General's report, and another to account for cigarette advertising restrictions implemented in 1968.

Douglas (1998) included smoking intensity as a proxy for addiction. He argued: 'If the notion that cigarettes are an addictive good needs any further support, it is provided by the negative and significant coefficient on the number of cigarettes smoked in a peak period ***(Cigarettes)*** in the quitting hazard function, although to the extent that ***Cigarettes*** may be endogenous, this coefficient is suspect'.

Peretti-Watel (2004) included onset age (time-invariant variable) as a proxy for addiction, but admitted in the discussion that age onset may be a poor proxy for potential addiction. Peretti-Watel (2004) result was counter-intuitive: onset age was negatively correlated with smoking cessation for males and females, indicating that the later in life a person starts to smoke, the less likely they were to quit. Peretti-Watel (2004) controlled for pregnant women and households with children. He assumed that pregnancy was a strong incentive to quit, and that this incentive was effective as soon as the pregnancy was known. He found that pregnant women, husbands or partners of pregnant women, and parents were more likely to quit smoking.

Tauras & Chaloupka (1999) and Tauras (1999) found that both males and females with strong attachments to religion, as measured by participation in religious services (never, infrequent, moderate, and frequent), were more likely to quit smoking than individuals with less religious attachment.

Tauras (1999) included parental education and mother's working status when the respondent was growing up. Tauras (1999) found that individuals whose mothers had at least some college education were much more likely to quit smoking as young adults than were individuals whose mother's education did not exceed the high school level. No significant differences were observed between paternal education and the probability of smoking cessation.

Individuals whose mothers worked while they were growing up were less likely to quit smoking as young adults than individuals whose mothers did not work while they were growing up.

Results from previous studies

In general, the results on the effect of price on the decision to quit smoking were mixed. Both Tauras & Chaloupka (1999) and Tauras (1999) found that prices were a significant determinant of smoking cessation. Tauras (1999) found that the estimated price elasticities from the Cox and Gompertz models were similar. The Cox elasticities ranged from 0.27 to 0.47 with an average elasticity of 0.35, whereas the Gompertz elasticities ranged from 0.25 to 0.46 with an average elasticity of 0.34. These estimates imply that a 10% increase in the real price of cigarettes increased the probability of cessation among young adults by approximately 3.4% to 3.5%. Tauras & Chaloupka (1999), using a Cox proportional hazard model, found the price elasticity of male cessation ranges from 1.07 to 1.17, with an average elasticity of 1.12. The price elasticity of female smoking cessation ranged from 1.17 to 1.21, with an average elasticity of 1.19. These estimates implied that a 10% increase in the real price of cigarettes will increase the probability of smoking cessation by approximately 11.2% for young men and by 11.9% for young women.

Douglas (1998) found that current cigarette prices had an unexpected negative coefficient, but the results were not significant. However, he found that future price affected smokers' decision to quit. A possible explanation for the statistical insignificance of current prices is collinearity among past, current, and future prices. Douglas could have tested this by dropping past and future prices.

Kenkel, Lillard & Liu (2009) found that price effects for cessation were small in size and not statistically significant. These results, however, were sensitive to alternative specifications. The authors themselves noted that, since the results were not robust to reasonable re-specifications (e.g. dropping year squared), they were cautious about interpreting the results as reliable evidence. Kenkel, Lillard & Liu (2009) also noted that there were very few male quitters in their sample (number not reported). The authors reported that the ratio of former smokers to ever-smokers was only about 0.06, whereas in the US this ratio had risen to about 0.5. The authors noted that 'our econometric model has low statistical power to detect influences that might help increase smoking cessation'.

Kostova, Husain & Chaloupka (2017) and Kenkel, Lillard & Liu (2009) concluded that higher prices did not encourage smoking cessation in China (small effect sizes and not statistically significant). This is likely because the rapid increase in average income have resulted in cigarettes becoming more affordable in China (Nargis et al., 2019). Kostova, Chaloupka &

Shang (2015) found that higher prices promoted cessation in UMICs but found no evidence that they did so in LMICs. Kidd & Hopkins (2004), who used the natural logarithm of price (the coefficient can be read directly as the elasticity of price), found no evidence that prices impacted the decision to quit. Madden (2007) also found that price was not statistically significant (results should be interpreted with caution as the sample was very small). Ross et al. (2014) found that a 10% increase in the excise tax increases the probability of smoking cessation by 1.6% to 2.3% in their study of Poland, Russia, and Ukraine.

Some authors did not interpret the coefficients estimated in their regression results, other than tax or price (Kostova, Chaloupka & Shang, 2015; Kostova, Husain & Chaloupka, 2017; Peretti-Watel, 2004). In all papers, except Tauras (1999) and Tauras & Chaloupka (1999), education was included as a time-invariant variable. While a time-invariant variable for education is problematic for smoking onset, it is less problematic for the quitting analysis, since the majority of smokers quit after they have achieved their highest level of education.

Higher education was positively associated with quitting (Douglas, 1998; Forster & Jones, 2001; Kidd & Hopkins, 2004; Kostova, Chaloupka & Shang, 2015; Peretti-Watel, 2004; Ross et al., 2014). Tauras & Chaloupka (1999) also found education, as measured by the number of years of formal schooling completed, was positively related to quitting for both males and females. However, the relationship was significant only for females. Tauras & Chaloupka (1999) found that females attending college full-time were more likely to quit smoking than females not attending college. Tauras (1999) found that individuals who attend college full-time were significantly more likely to quit smoking than were individuals who do not attend college at all, but that young adults with more years of secondary schooling were significantly less likely to quit than were those with fewer years of formal education.

Contrary to the results from the US, Madden (2007) noted: ‘Tax seems to be most effective in terms of encouraging quitting for those with the least education’. However, only nine quitters had the least education, so this statement should be read with caution.

Forster & Jones (2001) found that parental smoking, which is a strong predictor of smoking initiation, had little effect on quitting. Tauras & Chaloupka (1999) found that strong religious attachment (measured by religious service attendance) increased the likelihood of quitting for both males and females.

Douglas (1998) found that family income had a statistically significant positive association with quitting. Similarly, Kenkel, Lillard & Liu (2009) found that wealthier men (quartile 4 versus quartile 1) were more likely to quit. On the other hand, Tauras & Chaloupka

(1999) found no evidence that income impacts the probability of cessation for both males and females.

Tests for misspecification

Forster & Jones (2001) noted that previous studies (Tauras & Chaloupka, 1999) did not report whether the assumption of the proportional hazards was valid. If the assumption was invalid, parameter estimates of the elasticities would be inconsistent.

Few authors applied diagnostic tests (for example Cox–Snell residuals or Schoenfeld residual tests) to assess the fit of the empirical models of smoking cessation. When fitting their Cox proportional hazards models, Tauras and Chaloupka (1999) did not report whether the assumption of proportional hazards was valid for the data and parameters of their model. Douglas (1998) did not report the adequacy of the specification of his model.

Madden (2007), López Nicolás (2002), and Forster & Jones (2001) were the only authors who tested for misspecification. They analysed the cumulative Cox–Snell residuals arising from the models. A correctly fitted model should yield cumulative Cox–Snell residuals which resemble a censored sample from a standard exponential distribution. A plot of the nonparametric estimate of the cumulative hazard function for these data should therefore lie on a 45° line through the origin. Forster & Jones (2001) found little difference in the Cox-Snell residuals between the three models (the Cox, Weibull, and Generalised Gamma models) for both men and women, but concluded that the Generalised Gamma model performs slightly better.

Forster & Jones (2001) used Schoenfeld residuals to investigate the non-proportionality assumption in the Cox proportional hazards models. The tax variable failed the test for proportionality for the model estimated for men but passes for women (p-value of 0.06). Kidd & Hopkins (2004) used likelihood ratio tests to discriminate between split and non-split models and between pooled and sex-specific models. They found that the null hypothesis of equal slope coefficients was not rejected at the 5 per cent level; therefore they only presented pooled results. Madden (2007) used Cox-Snell residuals and found that the model is misspecified (the residuals deviate from the 45° line.

DATA

Smoking behaviour data

Smoking behaviour data are drawn from five waves of the National Income Dynamics Study (NIDS), which is the first nationally representative household panel study in South Africa (Southern Africa Labour and Development Research Unit). NIDS focuses on income, consumption, expenditure, health, education, fertility, and mortality. A stratified, two-stage cluster sample design was used to sample the households included in the base wave (Leibbrandt, Woolard & De Villiers, 2009). Since the sample was not designed to be representative at the provincial level (Leibbrandt, Woolard & De Villiers, 2009), I did not include a provincial variable in the analysis. In addition, provincial-level prices are only available from January 2008.

Although the data are longitudinal, I did not use the longitudinal characteristics of the data, as the change in the real price of cigarettes between waves was modest, for example, only 2% per year between 2008 (wave 1) and 2017 (wave 2). Instead, I combined data from all five waves to increase the sample size. Although individuals could have been interviewed up to five times, the same individuals across waves were entered only once in the study sample. The observation used when a respondent was interviewed more than once is explained in detail in the methods section.

There are five consistently worded smoking-related questions in NIDS waves 1−5. The smoking behaviour questions were used to create the pseudo-panel. There are three possible states:

1. **Current smokers** were asked three questions: ‘Do you smoke cigarettes?’, ‘How old were you when you first smoked cigarettes’, and ‘On average, how many cigarettes per day do you smoke?’
2. **Never-smokers** were asked two questions: ‘Do you smoke cigarettes?’ and ‘Did you ever smoke cigarettes regularly?’
3. **Quitters** were asked all five questions: ‘Do you smoke cigarettes?’, ‘Did you ever smoke cigarettes regularly?’, ‘How old were you when you last smoked cigarettes regularly?’, ‘How old were you when you first smoked cigarettes?’, and ‘On average, how many cigarettes per day did you smoke?’

Only current smokers and quitters were used in the analysis. Never-smokers were excluded from the dataset.

Since the NIDS data include birth month and year, the year of smoking onset and cessation could be calculated. NIDS also included interview month and year. These data enabled the analysis to be done monthly, instead of annually (which is less precise). For example, if a person was born in March 1993, and was interviewed in February 2017, then he was aged 23 years when he was interviewed. He reported started smoking at age 15. If price data were matched on an annual basis, then his starting year could be 2008 when he was aged 15 (from March to December 2008), or 2009 when he was still aged 15 (January and February 2009). Doing the analysis by calendar year could result in the year being incorrectly matched by one year for onset or cessation, or both. Since respondents were not asked in what month they started or quit smoking, an assumption about the start and quit months is made (see 'Uniform draw for start and quit month' in the methods section).

Index for monthly cigarette prices

Following several authors (Douglas, 1998; Kenkel, Lillard & Liu, 2009; Kostova, Chaloupka & Shang, 2015; Kostova, Husain & Chaloupka, 2017; Tauras, 1999; Tauras & Chaloupka, 1999), I used cigarette prices instead of taxes (Forster & Jones, 2001; Madden, 2007; Ross et al., 2014). Since excise taxes in South Africa are set at a national level, prices across the country do not vary drastically by province, so I did not encounter the complexity of state variation that occurs with US data.

CPI data for tobacco and CPI data for 'all items' were collated from several Excel files downloaded from Statistics South Africa's (Stats SA) website. Stats SA data require substantial collation as there are many files. For example, one file covers the period January 1970 to December 1979, and another covers January 1980 to December 1989. Data collation is presented graphically in Table 2.4. The geographical coverage and the label for tobacco products have changed over the decades. From January 1997, the category 'Metropolitan and other urban areas' was introduced. I used 'total country' values and work backwards, obtaining the widest geographical coverage available.

I used an index instead of prices for several reasons. An index is replicable: CPI monthly data are available online, whereas monthly cigarette price data are not. Secondly, monthly cigarette prices are only available from January 2000, and data for 2006 and 2007 do not exist as Stats SA's system was updated over that period. Thirdly, the Most Popular Price Category (MPPC) – a classification that reflects the average price of a pack of 20 cigarettes – is no longer a good measure of average cigarette prices. This is because illicit trade has become significant in South Africa since 2010, increasing the range of cigarette prices.

Table 2.4: Collation of CPI tobacco and CPI all items

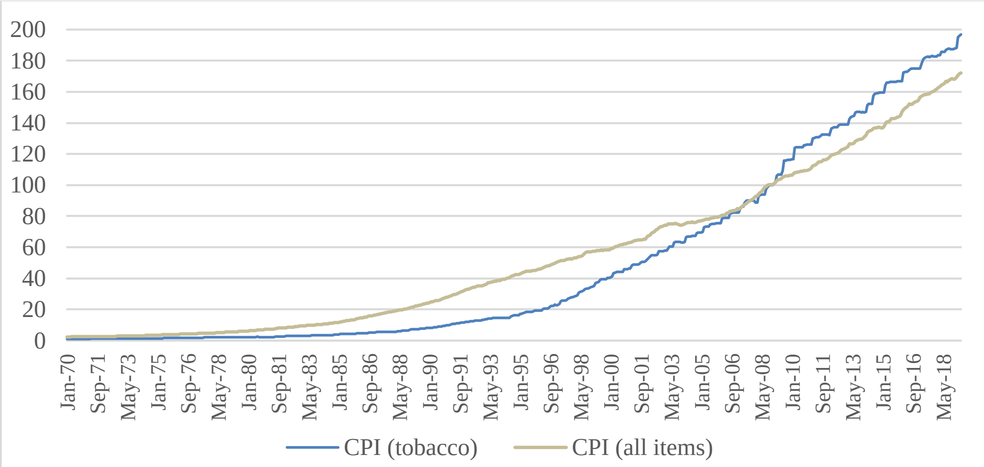
	CPI from various Stats SA Excel files					Consolidated CPI (for tobacco and all items)
	SARS label: Geographical coverage	Metropolitan	Metropolitan & other urban areas	Metropolitan & other & rural	Total country	
Date	SARS label: CPI tobacco	Cigarettes, cigars and tobacco	Cigarettes, cigars and tobacco	Cigarettes, cigars and tobacco	Tobacco	
Jan-70 Dec-96						
Jan-97 Dec-01						
Jan-02 Dec-07						
Jan-08						
May-19						

Tobacco CPI might suffer from bias if Stats SA does not capture a sufficient number of discount cigarettes. To the extent that Stats SA accurately collects the prices of the different categories of cigarettes (premium, MPPC and discount), the CPI will be a better reflection of the average price than the MPPC.

Prior to 2011, the MPPC constituted about three-quarters of the market. Premium cigarettes were slightly more expensive, and discount cigarettes slightly cheaper, than the MPPC. Since 2010, the illicit market has soared, and is estimated to be around 30−35% in 2017 (chapter 4 of this thesis). The increase in cheap cigarettes has decreased the MPPC market share. New cigarette manufacturers have been offering lower prices (often not paying excise tax), which has vastly expanded the range of low-priced cigarettes.

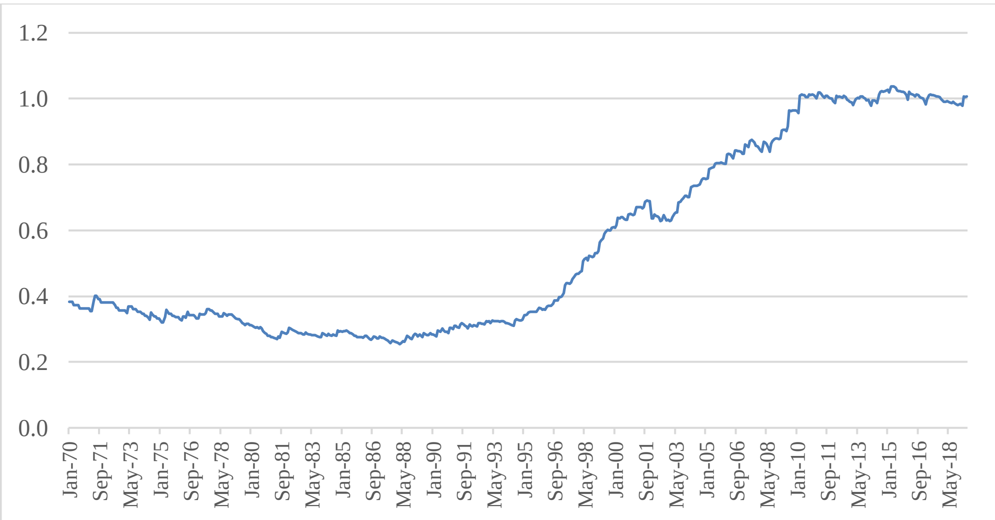
The inaccuracy of the MPPC in recent years is shown in this example: in 2017, the nominal price of an average pack of 20 cigarettes was estimated to be R36.60 by Stats SA. NIDS wave 5 (2017) includes a question on the price smokers paid at their last cigarette purchase. The average price in 2017 using weighted NIDS data were R33.03, with a large standard deviation of R15.04. Anecdotal evidence suggests that Stats SA may not have updated their sampling strategy to include the expansion of informally-sold cigarettes. Instead of using MPPI, CPI tobacco and CPI all-items data were collated from Stats SA. Figure 2.3 shows that the tobacco CPI increased at a faster rate from around 1994 to 2010 compared to the all-items CPI. After 2010, the rate is similar.

Figure 2.3: CPI tobacco and CPI all items (Dec 2008=100)



An index for monthly *real* cigarette prices was calculated by dividing CPI tobacco by CPI all items (Figure 2.4). The base month for the two variables is consistent (December 2016). In the 1970s and up to 1988, real cigarette prices decreased. In March 1988, real cigarette prices were at their lowest. From April 1988, real cigarette prices started to increase. Significant increases came in 1994 following a strong excise tax policy and the tobacco industry's pricing strategy. Although I have more recent data, I only used prices up to December 2017, as this is when data collection for NIDS 2017 concluded.

Figure 2.4: Real cigarette price index (CPI tobacco / CPI all items)



Price exogeneity

Generally, price elasticity estimates may be biased because of the endogeneity of the price variable. While the consumer is unable to influence the price that is charged by retailers, the consumer can choose to buy a cheaper or a more expensive pack. Given the way that South Africa's excise tax is levied (uniform specific), there is no tax variation across legal brands. Price variation is more likely than tax variation to be endogenously related to unobserved demand heterogeneity within an area over time. Guindon, Paraje & Chávez (2018) also used survey data, a price index, and survival analysis techniques. They noted that price endogeneity was not problematic using this method because (1) when using survey data, no individual tobacco user consumes enough to influence the market price, and (2) price endogeneity may be problematic when self-reported prices are used. The same logic applies to the current analysis. Prices were therefore considered to be exogenous.

METHODS

Merging NIDS datasets

All data analysis was conducted on Stata version 16.0. I used the following versions of the NIDS data: W1 version 7.0.0, W2 version 4.0.0, W3 version 3.0.0, W4 version 2.0.0, and W5 version 1.0.0. For each of the five waves, the 'adult' data file was merged with the 'hhderived', 'indderived', and 'link' data files. The 'adult' files contain most of the variables used in the analysis, including the smoking-related questions, as well as demographic questions. The 'indderived' files contain variables such as 'best age' and 'best education'. The 'hhderived' files contain the design weight variables, as well as geographic area (urban/rural). The 'link' files contain variables on the outcome of interviews across the waves (interview successfully completed or not). After merging the files by wave, fourteen-year-olds were excluded from the analysis (W1: n=61, W2: n=50, W3: n=15, none in W4 and W5) as they were not supposed to be interviewed (the adult questionnaire was for those aged 15 and older). The five waves were then merged using the person identifier variable 'pid'. The initial sample consisted of 40 134 respondents.

Although the NIDS data are longitudinal, I did not use the longitudinal characteristics of the data, because (1) the time frame would have been a lot shorter (2008 to 2017, instead of 1970 to 2017), and (2) the change in the real cigarette CPI between the NIDS waves was modest (only 1.8% per year between 2008 and 2017) as price variation mostly occurred before 2010; after

2010, prices remained relatively flat (see Figure 2.4.) Instead, I combined data from all fives waves to increase the sample size.

Possible combinations

There are 32 possible combinations of how respondents were tracked over time: interviewed in one wave only (5 possibilities), interviewed in two waves (10), in three waves (10), in four waves (5), in all five waves (1), or not interviewed in any wave (1) (Table 2.5). In total, there were 40 134 unique sampled respondents. 13 701 were successfully interviewed in one wave only (W1:2121, W2:1675, W3:1569, W4:2665, or W5:5671). 6870 respondents were successfully interviewed in two waves, 5047 in three waves, 5437 in four waves, and 6830 in all five waves. 2249 sampled respondents were not successfully interviewed in any of the waves. These numbers are for completed interviews, but there was some non-response (for example 'refuse to answer' or 'don't know') in the smoking-behaviour variables.

Table 2.5: Possible combinations of responses across five waves

	Wave 1	**Wave 2**	**Wave 3**	**Wave 4**	**Wave 5**	**n**
1 wave	1	.	.	.	.	2121
	.	1	.	.	.	1675
	.	.	1	.	.	1569
	.	.	.	1	.	2665
	.	.	.	.	1	5671
2 waves	1	1	.	.	.	935
	1	.	1	.	.	205
	1	.	.	1	.	108
	1	.	.	.	1	84
	.	1	1	.	.	781
	.	1	.	1	.	236
	.	1	.	.	1	149
	.	.	1	1	.	733
	.	.	1	.	1	239
	.	.	.	1	1	3400
3 waves	1	1	1	.	.	849
	1	1	.	1	.	257
	1	1	.	.	1	169
	.	1	1	1	.	629
	.	1	1	.	1	252
	.	.	1	1	1	1797
	.	1	.	1	1	460
	1	.	1	1	.	221
	1	.	.	1	1	320
	1	.	1	.	1	93
4 waves	1	1	1	1	.	1009
	.	1	1	1	1	2057
	1	.	1	1	1	1059
	1	1	.	1	1	960
	1	1	1	.	1	352
All waves	1	1	1	1	1	6830
No waves	.	.	.	.	.	2249
Total						**40134**

Data recoding and cleaning

Codes for ‘don’t know’ (-9) and ‘refused’ (-8) for all variables were recoded to missing (.). Respondents who said they quit smoking before they started (e.g., started smoking at 20, and quit smoking at age 15), were deleted from the dataset (W1: n=6, W2: n=15, W3: n=22). Respondents who said they quit at an age greater than age at interview were also deleted (W1: n=12, W2: n=1, W3: n=3, W4: n=7, W5: n=6).

Onset age, quit age, and explanatory variables

As is typical of panel studies, there are sometimes substantial differences in respondents’ answers about their smoking behaviour between waves. These measurement errors are the result of people not accurately remembering or reporting their exact age when they started or quit smoking, or because they did not answer truthfully. Given the stigma attached to smoking in some communities, respondents may lie about their smoking behaviour, especially if a family member was present during the interview.

Considering the various combinations presented in Table 2.5, age of onset and cessation were estimated using several waves of data. A person was coded as an ever-smoker if he or she indicated in at least one wave that he or she was a current or former smoker (n=10 024). For respondents who were interviewed only once, the data remained unchanged.

Where there were data from more than one wave, respondents who changed their onset and quit age answers drastically between waves were deleted. If a respondent said they started smoking at age 10 in W1, and age 17 in W2 (17−10=7), they were dropped from the sample. A cut-off point of 7+ years for onset was chosen. This resulted in 11.9% (1191/9995) of observations being dropped (Table 2.6).

The same was done for cessation age, but the cut-off point is 4+ years, resulting in 8.7% (179/2056) of observations dropped. The cut-off point for cessation was smaller because cessation was a more recent event, reducing recall error. This was first pointed out by Douglas (1998) who noted that imperfect recall was more pronounced with respect to the starting hazard than the quitting hazard, since all respondents quit smoking more recently than they started. The disadvantage of this data cleaning is that a relatively large number of observations were deleted. The advantage is that the remaining data were cleaner.

Table 2.6: Cut-off point for discrepancies in onset and cessation ages given across waves

	Onset			Cessation		
Age range (largest minus smallest)	Frequency	Per cent	Cumulative per cent	Frequency	Per cent	Cumulative per cent
0	5762	57.7	57.7	1750	85.1	85.1
1	730	7.3	65.0	53	2.6	87.7
2	675	6.8	71.7	50	2.4	90.1
3	558	5.6	77.3	24	1.2	91.3
4	442	4.4	81.7	22	1.1	92.4
5	380	3.8	85.5	22	1.1	93.4
6	257	2.6	88.1	15	0.7	94.2
7	227	2.3	90.4	22	1.1	95.2
8	152	1.5	91.9	15	0.7	96.0
9	127	1.3	93.2	12	0.6	96.6
10	133	1.3	94.5	6	0.3	96.8
11	77	0.8	95.3	7	0.3	97.2
12	71	0.7	96.0	8	0.4	97.6
13	54	0.5	96.5	5	0.2	97.8
14	44	0.4	96.9	6	0.3	98.1
15	54	0.5	97.5	6	0.3	98.4
16	31	0.3	97.8	4	0.2	98.6
17	29	0.3	98.1	3	0.2	98.7
18	16	0.2	98.2	4	0.2	98.9
19	17	0.2	98.4	3	0.2	99.1
20	25	0.3	98.7	1	0.1	99.1
21	13	0.1	98.8	2	0.1	99.2
22	13	0.1	98.9	1	0.1	99.3
23	15	0.2	99.1	2	0.1	99.4
24	11	0.1	99.2	1	0.1	99.4
25	5	0.1	99.2	1	0.1	99.5
26	8	0.1	99.3	3	0.2	99.6
27	11	0.1	99.4			
28	4	0.0	99.5			
29	4	0.0	99.5			
30	9	0.1	99.6			
31	6	0.1	99.7			
32	5	0.1	99.7	1	0.1	99.7
33	1	0.0	99.7	1	0.1	99.7
34	4	0.0	99.8			
35	4	0.0	99.8	2	0.1	99.8
36	3	0.0	99.8	1	0.1	99.9
37	2	0.0	99.8			
38	1	0.0	99.9			
39	3	0.0	99.9			
40	3	0.0	99.9			
41				1	0.1	99.9
42	1	0.0	99.9			
43	2	0.0	99.9	1	0.1	100.0
44						
46	3	0.0	100.0			
47	1	0.0	100.0			
54	1	0.0	100.0			
58						
105	1	0.0	100.0	1	0.1	100.0
Total	9995	100.0		2056	100.0	

Notes: Grey numbers indicate deleted observations. Observations for onset were deleted before observations for quitting were deleted.

To calculate onset age and cessation age (for quitters), the median ages across waves were used (Table 2.7). For example, if a respondent reported starting smoking at age 16 in W1 and age 15 in W5, and was not interviewed in any other waves, onset age was estimated to be 15.5 years. Although respondents could have started smoking again at a later stage, people who may have relapsed were not accounted for.

Table 2.7: Construction of age onset variable using data from all five NIDS waves

pid	W1	W2	W3	W4	W5	Age onset
301824	.	.	.	18	.	**18**
301825	16	.	.	15	.	**15.5**
301830	17	18	19	16	15	**17**
301835	.	20	25	21	25	**23**
301836	20	20	.	20	19	**20**
301855	14	17	.	.	.	**15.5**
301868	.	23	23	23	23	**23**
301888	.	.	18	22	17	**18**
301907	19	.	19	16	17	**18**
301975	19	.	16	.	13	**16**

The sex and race variables were straightforward, and answers did not change across waves. Information on race was missing for 10 respondents, who were dropped from the dataset. Asians were grouped with Whites since there were very few Asians in the sample (n=122). As will be shown later, the survivor functions of Asians and Whites were not statistically different. Education was defined as 0: Complete primary or less (including no education), 1: Complete secondary school (grade 12) and incomplete secondary, and 2: Tertiary (including incomplete tertiary).

Monthly per capita income in each wave was calculated by dividing total monthly household income by the number of people in the household (including children). Income across the five waves was adjusted for inflation using 2016 as the base year. The average income over the five waves was then calculated. This is a very crude estimate, as income tends to differ widely across waves as people move in and out of employment (Table 2.8). I chose tertiles as these three groups were statistically different, unlike the quartile and quintile groups where the middle groups were not statistically different from each other (2 and 3 for quartiles, and 2, 3, and 4 for quintiles). The three income tertiles are R22 to R905, R906 to R1847, and R1848 to R198 487.

Table 2.8: Per capita monthly household income (2016 prices)

pid	W1	W2	W3	W4	W5	Income
301016	4 936	.	300	16 304	.	**7 180**
301018	1 936	.	.	.	.	**1 936**
301027	1 472	1 892	3 205	2 106	2 405	**2 216**
301045	1 551	1 610	725	1 642	5 002	**2 106**
301047	5 515	2 768	.	4 952	.	**4 412**
301048	10 620	14 842	9 777	.	.	**11 746**

For each wave, religion was coded as 0 if a person did not follow any religion, and 1 if a respondent was Christian, Jewish, Muslim, Hindu, African traditional, or other. The median answer was calculated across waves (Table 2.9). If a person, for example pid 309662, said he conformed to a religion in waves 1 and 2, and no religion in waves 3 and 4, the median was 0.5. I assigned these respondents (5.9% of the sample) to the no religion category.

Table 2.9: Construction of religion variable

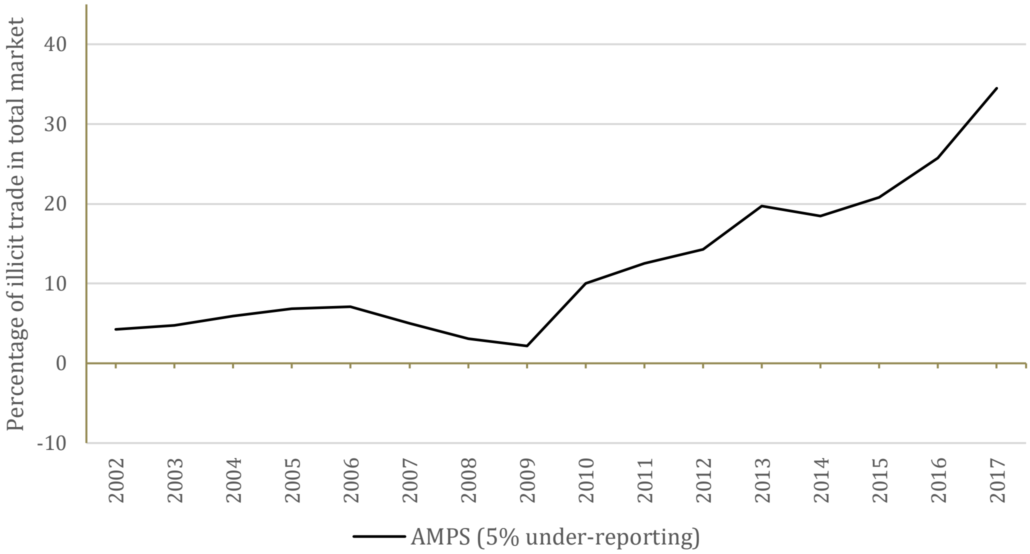
pid	W1	W2	W3	W4	W5	Median	Religion
309661	1	1	1	1	1	1	**1**
309662	1	1	0	0		0.5	**0**
309663	1	1	1	1	.	1	**1**
309664	1	.		1	0	1	**1**
309855	1	.	.	.	.	1	**1**
309945	0	.	1	.	.	0.5	**0**
310398	0	1	0	0	0	0	**0**

It was not possible to include Jewish, Muslim, Hindu, and other religions as distinct categories in the religion variable as the sample sizes were too small. For example, in wave 5, there were only 45 Muslim ever-smokers, 8 of whom had quit. The numbers were even lower for Jewish, Hindu, and other ever-smokers. Although the sample size for African traditional beliefs was relatively large (n=329 in wave 5), there was no statistical difference in the survival curves between ‘religion’ and ‘African traditional beliefs’, so they were grouped together.

For each wave, the ‘urban’ variable was coded as 0 if the respondent lived in a traditional or farm area, and 1 if he/she lived in an urban area. The median response was taken across waves. For median answers of 0.5 (1.6% of the sample), respondents were assigned to the urban category.

To account for the rise in illicit trade from 2010, an illicit trade variable was included in the analysis. Large price differences between cigarette brands may encourage smokers to switch to low-priced cigarettes instead of quitting. Estimates of illicit trade were drawn from chapter 4 of this thesis (Figure 2.5). Illicit trade was assumed to have been 1% in 2000, and 2% in 2001. Prior to 2000, illicit trade was assumed to equal zero. A continuous variable was used in the regression analysis. For the logrank test, I used a dichotomous variable equal to 0 from 1970 to 2010 (when illicit trade was low), and equal to 1 from 2010 to 2017 (when illicit trade was high).

Figure 2.5: Percentage of illicit trade in the total market: 2002–2017



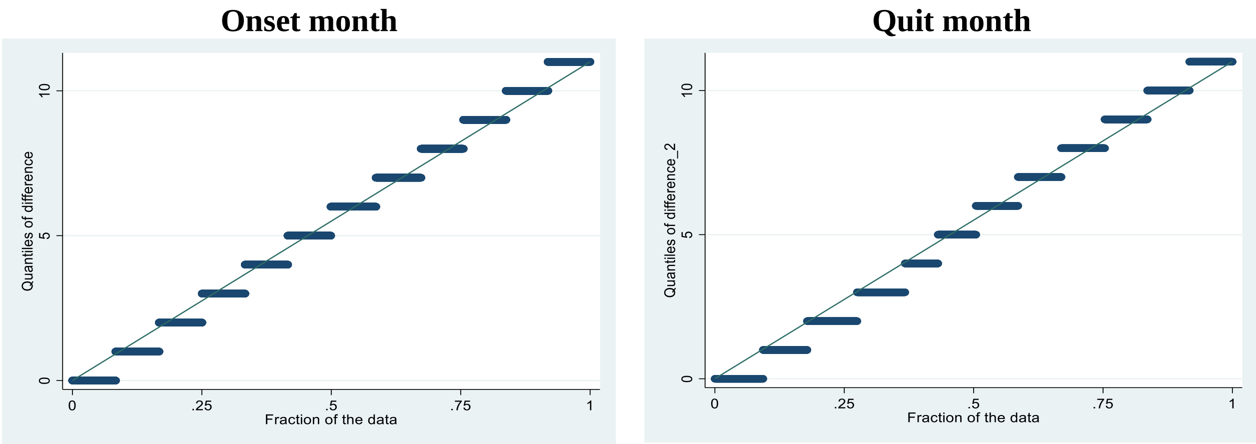
Source: Chapter 4 of this thesis.

Uniform draw for start and quit month

NIDS has information on interview date, respondents' birth month and year, respondents' age at the time of interview, smoking onset age, and smoking cessation age. Using this information, it was possible to bound the age of smoking onset and age of smoking cessation within a 12-month interval. For example, a person interviewed on 26 April 2017, born September 1977, aged 39 at the time of interview, and started smoking at age 20, would have started smoking in the 12-month interval from September 1997 to August 1998.

Following Guindon, Paraje & Chávez (2018), Guindon, Paraje & Chaloupka (2019), and Gonzalez-Rozada & Montamat (2019), a uniform distribution was used to randomly select the month of smoking onset and smoking cessation (Figure 2.6). A 12-month interval is relatively precise compared to previous studies. Guindon, Paraje & Chávez (2018) did not have birth month, so they were only able to bound the age of onset within 24 months (or 12 months when age and age of smoking onset were the same). Guindon, Paraje & Chaloupka (2019) had neither month of interview (October, November, or December) nor birth month so they randomly selected interview month and birth month for each individual.

Figure 2.6: Randomising month for onset age, and randomising month for cessation age



After the uniform draws were done, ever-smokers (n=786) who started smoking before January 1970 were dropped because an index for monthly cigarette prices exists only from January 1970. This follows López Nicolás (2002), who dropped respondents who started smoking before 1957 (from when price data were available). As a sensitivity analysis, I kept these 786 individuals, who enter the risk set from January 1970 (see sensitivity analysis section). The final sample consists of 7687 respondents (Table 2.10).

Table 2.10: Construction of final sample

Initial sample	**40 134**
Respondents deleted:	
Not interviewed in any waves	2 249
Cleaning within waves	
W1: Age onset > age cessation	6
W2: Age onset > age cessation	15
W3: Age onset > age cessation	22
W1: Age cessation > age at interview	12
W2: Age cessation > age at interview	1
W3: Age cessation > age at interview	3
W4: Age cessation > age at interview	7
W5: Age cessation > age at interview	6
Cleaning across waves	
Smoking onset age discrepancy between waves too large	1 191
Quitting age discrepancy between waves too large	179
Age onset > age cessation	57
No data on onset age	49
Never-smokers	27 757
No data on population group	10
Age onset < 10 years	53
Birth month unknown	21
Age onset > age at interview	7
Respondents who initiated in same month as interview month	18
Onset month < Jan 1970 (no monthly CPI data available)	784
Final sample	**7 687**

Expanding data and Stset

Cross-section information was transformed into multiple records for each individual. Some variables remained the same (sex, race, urban/rural), while others varied with time (e.g., price, illicit trade). The data were expanded for each individual by the number of months since they started smoking. The event indicator 'QUIT' indicates whether quitting occurred in that time period (0 = did not quit, 1 = quit). For each smoker who quit, the event indicator is 0 in every record except the last. These non-censored individuals experience the event in their last recorded period, when the event takes on a value of 1. Censored individuals never experienced the event so the event remains 0 throughout (Singer & Willett, 2003).

The `stset` command informs Stata about the structure of the survival data. The `stset` command requires the user to define the onset of the risk of failure and analysis time. I used the command `stset end, failure(QUIT) origin(time begin) id(pid)`. The first variable 'end' tells Stata when the end of time is. The end of time is either when a person quits, or for continuing smokers, when the most recent data were collected (right-censored data). Most recent data could be W1, W2, W3, W4, or W5 (see Table 2.5). 'QUIT' is the failure event variable. The personal identifier variable 'pid' distinguishes one person from another. The origin (beginning of time) is 'begin'. Each person's beginning of time is defined as the month he/she started smoking. Stata output (Figure 2.7) indicates that there were 7687 ever-smokers, and that the total number of time periods under observation was 1 453 494 months. 1447 ever-smokers quit smoking. The last observed exit time was month 575. Although it could have been one month higher (1970m1 – 2017m12 = 576 months), no respondent quit in the last month, as all failures had occurred by this time, and all the data were right-censored by t=575.

Figure 2.7: Stata output from ststet command

```
                id:  pid
     failure event:  QUIT != 0 & QUIT < .
obs. time interval:  (end[_n-1], end]
 exit on or before:  failure
    t for analysis:  (time-origin)
            origin:  time begin

------------------------------------------------------------------------------
  1,453,494  total observations
          0  exclusions
------------------------------------------------------------------------------
  1,453,494  observations remaining, representing
      7,687  subjects
      1,447  failures in single-failure-per-subject data
  1,453,494  total analysis time at risk and under observation
                                                 at risk from t =         0
                                      earliest observed entry t =         0
                                           last observed exit t =       575
```

After expanding the smoking behaviour data, price data were merged on calendar month. Consider smoker with pid 303411 (Table 2.11). He started smoking at age 15, quit at age 18, and was interviewed at age 23. He was born in March 1993 and interviewed in February 2017. There is a 12-month period when he was 15 during which he could have started smoking (March 2008 to February 2009). He was randomly assigned to February 2009. He could have quit from March 2010 to February 2011. He was randomly assigned October 2010.

Table 2.11: Event history for pid 303411

Age onset	Age quit	Age at last interview	Birth month	Last interview date	t	QUIT	CPI tobacco index
15	18	23	1993m3	2017m2	**2009m2**	0	0.88
15	18	23	1993m3	2017m2	2009m3	0	0.90
15	18	23	1993m3	2017m2	2009m4	0	0.91
15	18	23	1993m3	2017m2	2009m5	0	0.91
15	18	23	1993m3	2017m2	2009m6	0	0.90
15	18	23	1993m3	2017m2	2009m7	0	0.92
15	18	23	1993m3	2017m2	2009m8	0	0.96
15	18	23	1993m3	2017m2	2009m9	0	0.96
15	18	23	1993m3	2017m2	2009m10	0	0.97
15	18	23	1993m3	2017m2	2009m11	0	0.97
15	18	23	1993m3	2017m2	2009m12	0	0.96
15	18	23	1993m3	2017m2	2010m1	0	0.96
15	18	23	1993m3	2017m2	2010m2	0	0.96
15	18	23	1993m3	2017m2	2010m3	0	1.01
15	18	23	1993m3	2017m2	2010m4	0	1.01
15	18	23	1993m3	2017m2	2010m5	0	1.01
15	18	23	1993m3	2017m2	2010m6	0	1.01
15	18	23	1993m3	2017m2	2010m7	0	1.01
15	18	23	1993m3	2017m2	2010m8	0	1.00
15	18	23	1993m3	2017m2	2010m9	0	1.01
15	18	23	1993m3	2017m2	**2010m10**	**1**	1.01

Variables (TC_1995 and TC_2001) were created to account for tobacco control legislation that was implemented in August 1995 (written health warnings on packs), January 2001 (advertising ban), and July 2001 (smoke-free areas) (Little & van Walbeek, 2018; Van Walbeek, 2005). As with excise taxes, decisions regarding other tobacco control interventions were taken at the national level. TC_1995 is coded to zero prior to August 1995 and to 1 from August 1995. TC_2001 is coded to zero prior to January 2001 and to 1 from January 2001. TC_1995 and TC_2001 are used for the log-rank tests, which compare the observed and expected number of failures for each group (for more details on the log-rank test, see the results section). To account for the fact that these policies may have become less effective over time, additional variables were created for the regression analysis. These variables were coded to decrease at a decreasing rate (flattening from year 5). For the first twelve months following implementation (year 1), the variables are coded as 1, 0.5 in year 2, 0.33 in year 3, 0.25 in year 4, and 0.2 thereafter.

Weights

In some cases, sampling weights across waves varied markedly (Table 2.12). Respondent with pid 302632 represented 2563 people in 2008, 8160 in 2010, 5261 in 2012, and 9371 in 2015. In other cases, the weights were more stable. Respondent with pid 302683 was assigned a weight of 218 in 2008, 212 in 2012, and 314 in 2017.

Table 2.12: Sampling weighs of a random sample of respondents: Waves 1−5

pid	w1_wgt	w2_wgt	w3_wgt	w4_wgt	w5_wgt	Average
302632	**2 563**	**8 160**	**5 261**	**9 371**		**6 339**
302642	2 236		7 432	5 708	8 424	5 950
302643	180	110	276	246	153	193
302683	**218**		**212**		**314**	**248**
302684	932	1 060	520		692	801
302693	6 537	8 540	10 671			8 583
302709	866					866
302718	1 739	861		922	978	1 125

In the cessation literature, none of the authors applied weights to the analysis. In the smoking onset literature, applying weights to survival analysis was done in Argentina (Guindon, Paraje & Chávez, 2018). These authors ran the analysis with and without weights and found little difference in the results. If sampling weights are applied to the survival analysis estimation, then one sample weight per individual is used for each row of data, i.e., the weight does not vary over time. For example, if a male was interviewed in 2017, and he represented 1000 males, the weight of 1000 is applied to all previous periods. Table 2.13 shows population dynamics in South Africa over the past few decades. In 1970, Whites comprised 19% of the population, decreasing to around 8% in 2017 (Central Statistical Service, 9 April 1987; Statistics South Africa, 2017). NIDS is weighted on population group, sex, and age. Since the percentage of South Africans in each population group has changed over the past few decades, applying a weight of 1000 in 2017 and 1970 would not make sense, given the changing population dynamics. I used the average sampling weight in the descriptive statistics table, but not in the regressions analyses.

Table 2.13: Mid-year population estimates for South Africa, 1970 and 2017

	Total population in 1970	Percentage of total population in 1986	Total population in 2017	Percentage of total population in 2017
African	13 450 000	66.8	45 656 400	80.8
Coloured	2 170 000	10.8	4 962 900	8.8
Indian/Asian	655 000	3.3	1 409 100	2.5
White	3 870 000	19.2	4 493 500	8.0
Total	20 145 000	100	56 521 900	100

Sources: Central Statistical Service. 9 April 1987. Mid-year estimate: 1970−1986. http://www.statssa.gov.za/publications/P0302/P03021986.pdf; Statistics South Africa. 2017. Mid-year population estimates 2017. http://www.statssa.gov.za/publications/P0302/P03022017.pdf.

Regression analysis

Cox proportional hazard model (semi-parametric model)

The Cox proportional hazard model specifies a regression model with a specific functional form but does not specify the exact form of the distribution of event times (Allison, 1984). The Cox proportional hazards regression model (Cox, 1972) asserts that the hazard rate for the *j*th subject is:

$$h(t|\mathbf{x}_j) = h_0(t)\exp(\mathbf{x}_j\mathbf{b}) = h_0(t)\exp(b_1x_{1j} + b_2x_{2j} + \ldots + b_kx_{kj})$$

where $h_0(t)$ is the baseline hazard, $\exp(\mathbf{x}_j\mathbf{b})$ is the relative hazard, and $\mathbf{b} = (b_1, b_2, \ldots, b_k)$ is the set of coefficients on the independent variables to be estimated (Stata Netcourse 631, 2019). The Cox proportional hazards model has no intercept, because the intercept in subsumed in the baseline hazard.

Logit and cloglog models (non-parametric models)

To handle the hazard's upper and lower bounds of 0 and 1, logit and cloglog models transform the hazard to a different scale with no upper or lower bound. Transformation can improve distributional behaviour, prevent specification of inadmissible values, and render disparate values of hazard more easily comparable (Singer & Willett, 2003). The logit's and the cloglog's transformed version of the hazard are the dependent variables in a regression equation. The transformation used is called the 'link function' − the function that 'links' predictors to outcomes.

The baseline logit and cloglog hazard function is obtained when the value of the predictor is equal to 0. The effect of a predictor is to shift the baseline hazard function vertically. The size of the gap between the two functions obtained from a one-unit difference in the value of the predictor measures the size of the predictor's effect. The functional form of the baseline hazard function in the logit and the cloglog models can be estimated using time indicators (dummy variables), or a smooth polynomial specification.

Logit model

The discrete time hazard model with a logit link is specified as:

$$logit\ h(t_j) = [a_1d_1 + a_2d_2 + \cdots + a_jd_j] + [\beta_1X_1 + \beta_2X_2 + \cdots + \beta_PX_P]$$

where the model's left side presents a transformed version of the hazard (Singer & Willett, 2003). The logit model is specified as the natural logarithm of the odds: ln(*x*/(1−*x*))

(Gujarati, 2003). Natural logs (logarithms with base e) are preferred because coefficients on the natural-log scale are directly interpretable as approximate proportional differences (Gelman & Hill, 2007). All log transformations generate similar results, but the convention in applied econometrics is to use the natural log.

The odds ($x/(1-x)$) compare the probability (see life table: Table 2.18, column 7) that an event will occur and the probability that it will not occur. If the probability of event occurrence is 0.80, the probability that the event will not occur is 0.20. The associated odds are 80:20, or 4 to 1. The centre of the odds scale is 1.0. If a hazard probability is greater than 0.5, the odds of event occurrence are greater than 1; if the hazard probability is below 0.5, the odds of event occurrence are less than 1.0 (Singer & Willett, 2003).

The model's right-hand side is composed of two sets of terms. The first set of terms, the *a*s multiplied by their respective time indicators, act as multiple intercepts, one per period. Each intercept parameter, a_1, $a_2, \ldots\ldots,$ a_j, represents the value of the logit hazard in that particular time period for individuals in the baseline group. As a group, these parameters represent the baseline logit hazard function – the value of the logit hazard when all P substantive predictors are equal to 0. These parameters provide a flexible representation for the baseline logit hazard function. Each d represents a time period. The advantage of using a set of time indicators is that it does not presuppose a functional form. Each time indicator is set to 1 in the time period it represents and 0 elsewhere. For example, $d_1=1$ is the first time period and 0 thereafter; $d_2=1$ in the second time period and 0 in all other time periods, as shown in Table 2.14.

The second set of terms, the *β*s multiplied by their respective substantive predictors, represent the shift in the baseline hazard function corresponding to unit differences in the associated predictors. Each slope parameter, β_1, $\beta_{2}, \ldots\ldots,$ β_P, assesses the effect of a one-unit difference in that predictor on event occurrence, controlling for the effects of all other predictors in the model.

Using fewer time indicators

There are 575 *d*s in the monthly analysis (January 1970 to November 2017). There are no failures in the last time period, December 2017 (d_{576}). A dummy specification for the time at risk measured in 575 months requires the inclusion of a large number of unknown parameters. Like other authors (Guindon, Paraje & Chávez, 2018), I found the inclusion of 575 time indicators to be computationally demanding, and fraught with convergence problems. A way around this, but still keeping the analysis by month, is to group the *d*s into years. For example, time indicator D_1 is equal to 1 for time periods d_1 to d_{12} and 0 in all other periods, D_2 is equal to

1 for time periods d_{13} to d_{24} and 0 in all other periods (Table 2.14). This reduces the dummy variables to 48 instead of 575, and Stata does not encounter convergence issues. The analysis is therefore done using dummy indicators D_1 to D_{48}.

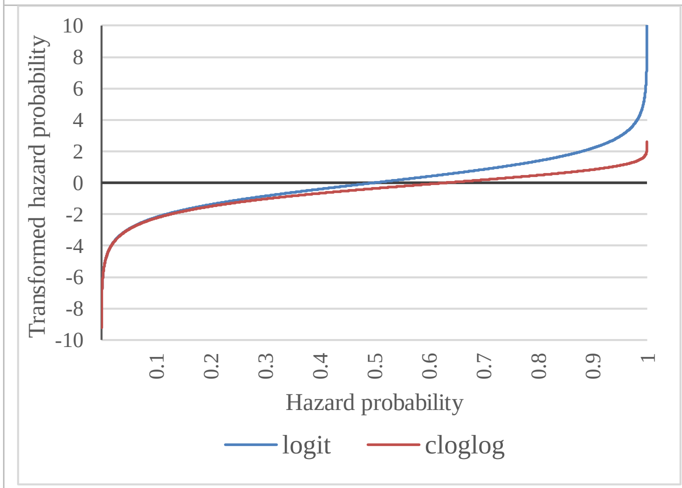
Table 2.14: Time indicators

	d_1	d_2	.	.	d_{11}	d_{12}	d_{13}	d_{14}	.	.	d_{23}	d_{24}	D_1	D_2
Jan-70	**1**	0	.	.	0	0	0	0	.	.	0	0	**1**	0
Feb-70	0	**1**	.	.	0	0	0	0	.	.	0	0	**1**	0
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
Nov-70	0	0	.	.	**1**	0	0	0	.	.	0	0	**1**	0
Dec-70	0	0	.	.	0	**1**	0	0	.	.	0	0	**1**	0
Jan-71	0	0	.	.	0	0	**1**	0	.	.	0	0	0	**1**
Feb-71	0	0	.	.	0	0	0	**1**	.	.	0	0	0	**1**
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
Nov-71	0	0	.	.	0	0	0	0	.	.	**1**	0	0	**1**
Dec-71	0	0	.	.	0	0	0	0	.	.	0	**1**	0	**1**

Complementary log log (cloglog) model

The complementary log-log function is sometimes used for discrete duration data (Box-Steffensmeier & Jones, 2004). For a given probability, the cloglog is specified as: cloglog=ln(−ln(1−probability)). The cloglog specification, unlike the logit, has a response curve that is asymmetric (Figure 2.8). The first and last five values depicted in Figure 2.8 are listed in Table 2.15.

Figure 2.8: Logit and cloglog transformations



Note: Transformed values are plotted for raw probabilities ranging from 0.0001 to 0.9999

Table 2.15: Logit and cloglog transformation

Hazard probability	Transformed hazard probability	
	logit	cloglog
x	ln(x/(1–x))	ln(–ln(1–x))
0.0001	-9.21	-9.21
0.0002	-8.52	-8.52
0.0003	-8.11	-8.11
0.0004	-7.82	-7.82
0.0005	-7.60	-7.60
.	.	.
.	.	.
.	.	.
0.9995	7.60	2.03
0.9996	7.82	2.06
0.9997	8.11	2.09
0.9998	8.52	2.14
0.9999	9.21	2.22

Similarly to the discrete time hazard model with a logit link model, the discrete time hazard model with a cloglog link is specified as:

$$cloglog\ h(t_j) = [a_1 d_1 + a_2 d_2 + \cdots + a_j d_j] + [\beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_P X_P]$$

When the hazard probability (x-axis) is small (less than 0.2), both transformed hazard probabilities (y-axis) yield similar values. At higher values of the hazard, the transformations diverge. The slope of the cloglog curve is less steep than the slope of the logit curve (Figure 2.8). In practice, cloglog and logistic hazard models that share the same duration dependence specification and same independent variables yield similar estimates, as long as the hazard rate is relatively small (Jenkins, 18 July 2005; Singer & Willett, 2003).

The advantage of using the cloglog transformation is that it provides a discrete-time model for hazard that has a built-in *proportional hazards* assumptions, and not a *proportional odds* assumption (as is the case with the logit link) (Singer & Willett, 2003). Results from the cloglog regression can be directly compared to those of the continuous-time Cox regression model that also invokes a *proportional hazards* assumption (Singer & Willett, 2003). An antilogged coefficient from a model with a logit link is an *odds ratio*; an antilogged coefficient from a model with a cloglog link is a *hazard ratio*. The odds ratios and the hazard ratios (also known as relative risks) are distinct, but interrelated, measures of effect size. One compares odds, the other hazards:

$$\text{Odds ratio} = \frac{h(t_j: group\ 1)/[1-h(t_j): group\ 1)]}{h(t_j: group\ 2)/[1-h(t_j): group\ 2)]}$$

$$\text{Hazard ratio} = \frac{h(t_j: group\ 1)}{h(t_j: group\ 2)}$$

An assumption inherent in the logit and cloglog models is that the distance between each of the hazard functions is identical in every time period − the gap cannot be larger in some periods and smaller in others. The effect of the predictor is assumed to be constant over time (Singer & Willett, 2003). This assumption may, or may not, hold in practice.

Smooth polynomial for time

Even though event occurrence has been recorded in discrete time, it is still possible to treat time as though it has a continuous specification in the discrete-time hazard model (Singer & Willett, 2003). In later time periods, the hazard rate is expected to be near zero because the risk of occurrence is low (usually because the risk set is very small). When few or no events occur, maximum likelihood model-fitting algorithms using a dummy specification may fail to converge, coefficient stability decreases, and parameter estimates take on implausible or impossible values (Singer & Willett, 2003). An alternative is to use a polynomial specification for the functional form. A basic specification is:

$$logit\ h(t_j) = \beta_1 Price + \beta_2 \boldsymbol{X} + a_1 t_1 + a_2 t_2 + a_3 t_3 + a_4 t_4$$

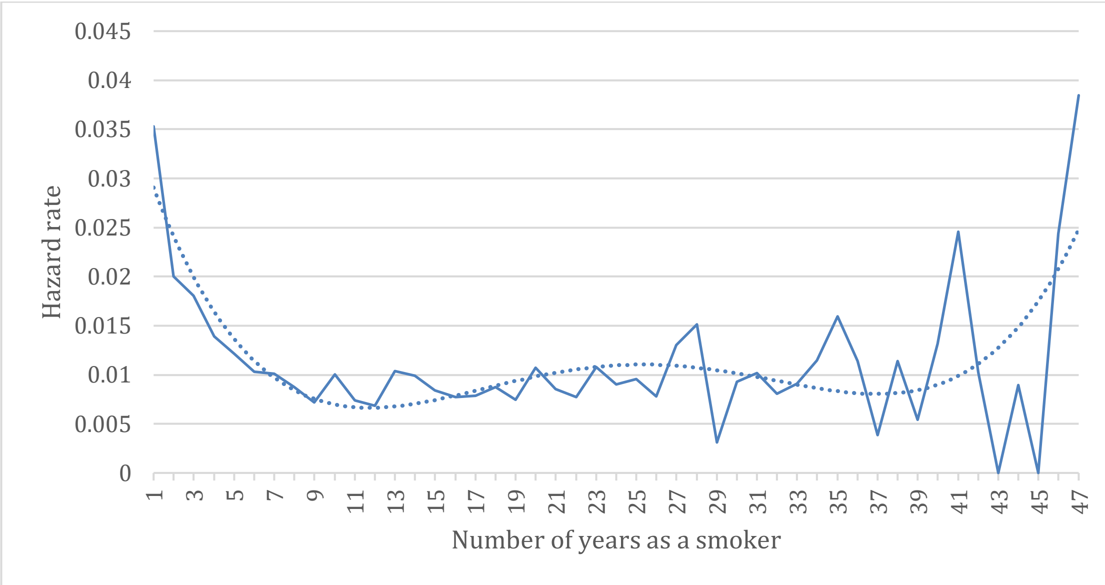
where the dependent variable is the event indicator (whether or not the respondent quit smoking in that time period), ***X*** is a matrix of demographic and socio-economic variables, and t_1, t_2, t_3, t_4 provide a fourth-order polynomial specification to account for duration dependency.

Choosing the order of the polynomial can be done using Akaike's information criterion (AIC) and Bayesian information criterion (BIC). AIC and BIC statistics provide a benchmark to compare models (Table 2.16). The AIC and BIC account for model complexity by combining a term reflecting how well the model fits the data with a term that penalizes the model in proportion to the number of its parameters. The specification with the lowest, or next lowest, AIC and BIC is often the best fit (Singer & Willett, 2003). For this reason, I chose a fourth order polynomial (Figure 2.9). The difference between a fourth and fifth order polynomial is very small (–1.4 AIC and BIC).

Table 2.16: Akaike's information criterion (AIC) and Bayesian information criterion (BIC)

Representation for time	AIC	Difference in AIC compared to previous model	BIC	Difference in BIC compared to previous model
Linear	22 776.8		22 801.2	
Quadratic	22 654.1	−122.7	22 690.7	−110.5
Cubic	22 595.5	−58.6	22 644.3	−46.4
Fourth order	22 572.5	−23.0	22 621.2	−23.0
Fifth order	22 571.0	−1.4	22 619.8	−1.4
Sixth order	22 569.0	−2.0	22 617.8	−2.0

Figure 2.9: Fourth order polynomial



RESULTS

Descriptive statistics

About 19% (n=1447) of ever-smokers in the sample quit smoking (Table 2.17). Since smoking prevalence was much higher among males than females, the sample was about three-quarters male and one-quarter female. In 2017, smoking prevalence was 34% among males and 7% among females (overall prevalence 19%) (Southern Africa Labour and Development Research Unit). The sample of ever-smokers (7687) consists of 61% African, 30% Coloured, and 10% White/Asian. NIDS 2017 weighted data indicates that the actual population was 82% African, 10% Coloured, 2% Asian, and 9% White/Asian. Coloured individuals were over-represented, as their smoking prevalence was the highest among the population groups: 40% compared to Africans (16%), and White/Asian (25%) (NIDS 2017 weighted data).

Only 13% of the sample of ever-smokers had some tertiary education. This was lower than the national average of 18%. This suggests that smoking is generally more prevalent among the less educated. The mean age of smoking onset was 18.4 years (standard deviation of 5.2), while the mean age of smoking cessation was 27.8 years (standard deviation of 11.3).

The weighted number of smokers was 10.2 million people. This is higher than individual waves (2008: 7.4 million, 2010: 6.5 million, 2012: 7.3 million, 2015: 7.9 million, 2017: 8.0 million) as a person was coded as a smoker if he or she indicated in at least one wave that he or she was a current smoker. People often changed their answers between waves. For example, a person who was an occasional smoker may have answered 'no' in one wave, and 'yes' in another. Given that the question ('Do you smoke cigarettes?') has no time frame, people may have interpreted the question differently from one wave to the next.

Table 2.17: Descriptive statistics of the sample of ever-smokers

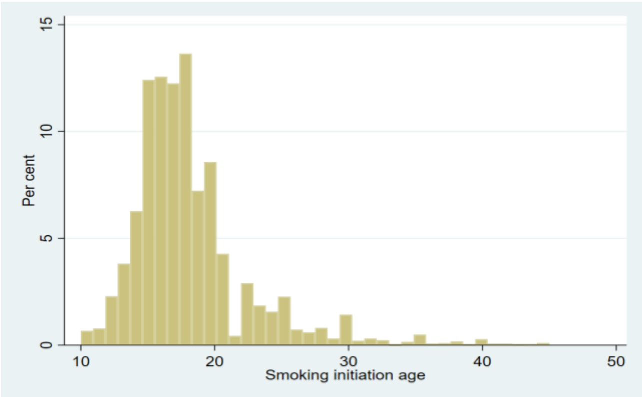
		Unweighted		**Weighted**	
Variable	**Description**	**n**	**%**	**n**	**%**
Total	Ever-smokers	7687	100	13 120 284	100
Quit	Yes	1447	18.8	2 909 000	22.2
	No	6240	81.2	10 211 284	77.8
Sex	Male	5630	73.2	3 239 930	25.7
	Female	2057	26.8	9 880 354	75.3
Race	African	4677	60.8	7 946 076	60.6
	Coloured	2272	29.6	2 485 802	19.0
	White/Asian	738	9.6	2 688 406	20.5
Education	Complete and incomplete primary (including no education)	1930	25.2	2 429 562	18.6
	Complete and incomplete secondary school (grade 12)	4774	62.2	8 289 269	63.3
	Complete and incomplete tertiary	971	12.7	2 376 492	18.2
Urban	Rural	2525	32.9	3 189 954	24.3
	Urban	5156	67.1	9 930 330	75.7
Religion	No religion	1096	14.3	1 978 003	15.1
	Religion	6576	85.7	11 108 351	84.9
Income	Tertile 1	2563	33.3	4 373 612	33.3
	Tertile 2	2562	33.3	4 384 694	33.4
	Tertile 3	2562	33.3	4 361 978	33.2
Age	Mean smoking onset age (std dev)	7687	18.4 years (5.2)	13 120 284	18.3 years (5.0)
	Mean smoking cessation age (std dev)	1447	27.8 years (11.3)	2 909 000	28.3 years (11.1)

Age of onset and age of quitting

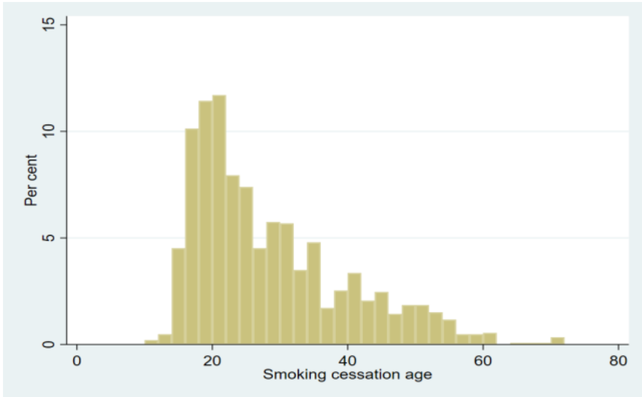
80% of ever-smokers in the unweighted sample had started smoking by age 20 (Figure 2.10). Fewer than 3% of the unweighted sample started smoking after age 30. The distribution of smoking cessation age is much wider. Of quitters, half quit by age 25, while 80% quit by age 37.

Figure 2.10: Smoking onset and cessation ages

Smoking onset age



Smoking cessation age



Life table

A life table is a useful tool to summarise quitting behaviour (Table 2.18). The time period t_0 reflects each individual's beginning of time. These dates differ by individual; for example, person *x* started smoking in February 1977, while person *y* started smoking in December 2015. Although, theoretically, an individual can start and quit in the same month, I do not allow for this. The first month that an individual can quit is t_1.

Table 2.18: Life table

Time period (Months as a smoker)	Time interval	Risk set - Number of respondents in each time period	**Event=0** Number of respondents who did not quit smoking	**Event=1** Number of respondents who quit smoking	Censored at the end of the year	Hazard function (Proportion of smokers who quit)	Survivor function (Proportion of smokers who haven't quit)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
t_0	[0,1)	7687	7687	0	–	–	1.000
t_1	[1,2)	7687	7661	26	6	0.003	0.997
t_2	[2,3)	7655	7618	37	4	0.005	0.992
t_3	[3,4)	7614	7581	33	15	0.004	0.988
t_4	[4,5)	7566	7544	22	11	0.003	0.985
t_5	[5,6)	7533	7517	16	11	0.002	0.983
t_6	[6,7)	7506	7479	27	17	0.004	0.979
t_7	[7,8)	7462	7441	21	11	0.003	0.976
t_8	[8,9)	7430	7411	19	14	0.003	0.974
t_9	[9,10)	7397	7375	22	15	0.003	0.971
t_{10}	[10,11)	7360	7342	18	10	0.002	0.968
.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.
t_{573}	[573,574)	1	1	0	0	0.000	0.555
t_{574}	[574,575)	1	1	0	1	0.000	0.555
Total		**1 453 494**	**1 452 047**	**1 447**	**6 240**		

The time intervals in column 2 reflect a standard partition of time in which each interval includes the initial time (e.g., first day of the first month) up until the concluding time (last day of the first month). The first day of the second month falls into the next interval. Square brackets denote inclusions; round brackets denote exclusions. Any event occurring between the first day of the first month up to (but excluding) the first day of the second month is classified as occurring during t_1. There are a total of 574 intervals [0,1) [1, 2), [2, 3), [3, 4), [4, 5),… [574, 575).

Some of the NIDS data are censored because of the age of respondents. A smoker who was aged 20 at the time of the interview can only be observed until age 20. If this person did not quit smoking by the time of the interview, then this observation will be censored.

The risk set declines because of both event occurrence and censoring. In t_1, 26 people quit smoking; 6 were censored, leaving 7655 (=7687–26–6) individuals to enter t_2. Once an individual quits smoking in one period, he or she drops out of the risk set in all future time periods and no longer contributes any more rows to the dataset. The risk set for t_2 is thus 7655 individuals. In the last interval, there is only one person in the risk set, who does not quit smoking (and is therefore censored).

In total, 1447 of the 7687 ever-smokers quit smoking. There are a total of 1 453 494 person-period observations, which is the summation of each period's risk set. The total observations (n=1 453 494) and the number of ever-smokers (n=7687) corresponds with the `stset` output (Figure 2.7). Of these, 1 042 842 are males and 410 652 are females (the difference is due to the higher smoking prevalence among males than females).

Column 7 of the life table (Table 2.18) shows the hazard rate in each time period (Figure 2.11). The data in Figure 2.11 were excluded after t_{480} because the hazard rate is artificially high in the later months, distorting the graph. For example, in t_{568}, the hazard rate is 0.091 (1 of 11 smokers quit smoking).

Figure 2.11: Hazard function: t_1 to t_{480} (Table 2.18 column 7)

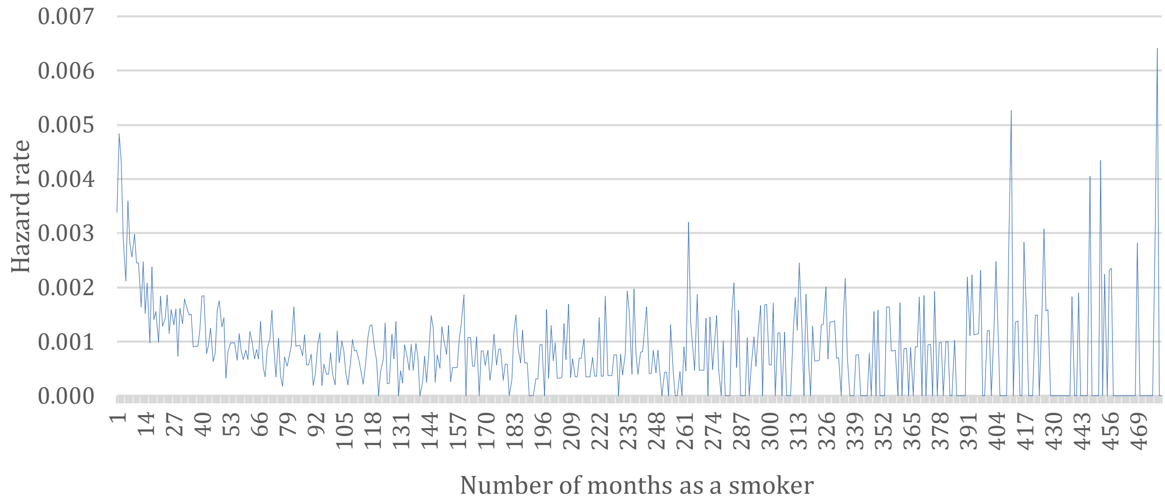
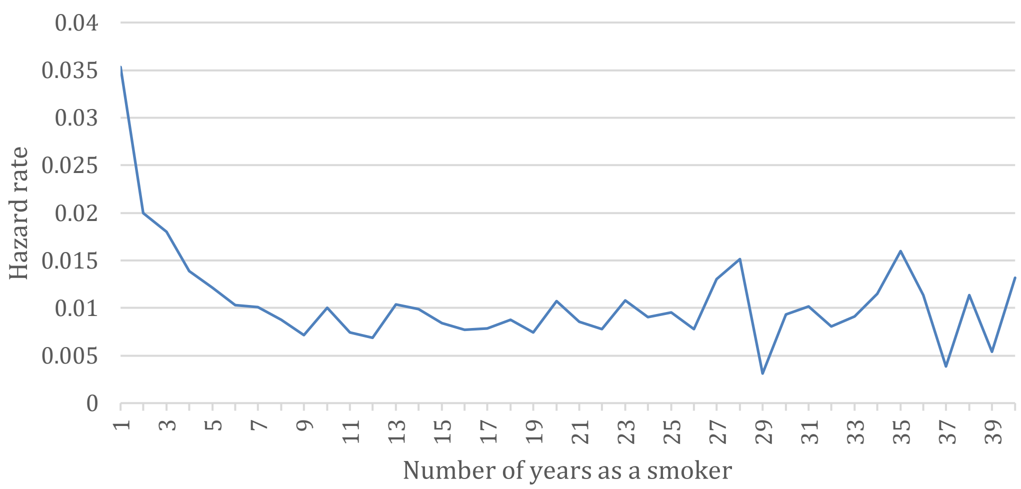
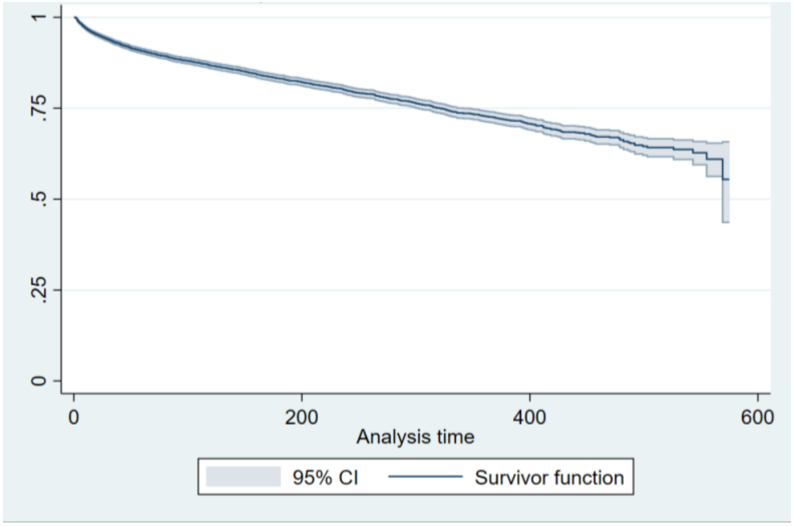


Figure 2.12: Hazard function: t_1 to t_{480} (grouped in years)



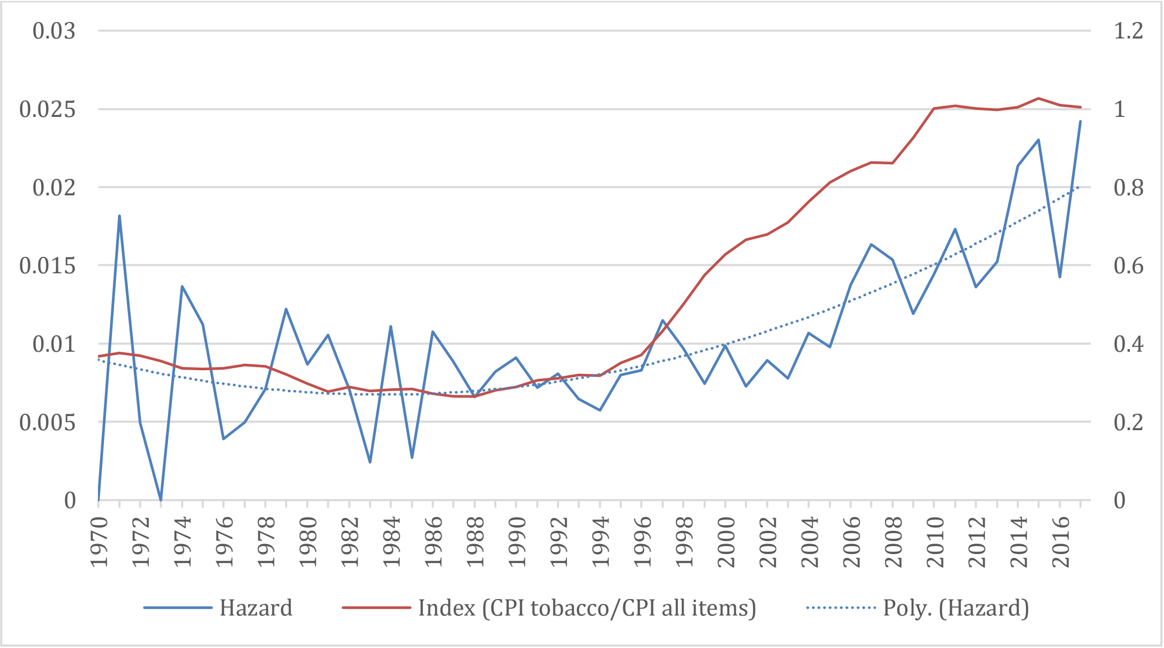
The Kaplan–Meier estimator of the survivor curve is non-parametric (no assumptions are made about the shape of the survivor curve) (Stata Netcourse 631, 2019). The survivor function presents the probability of survival beyond point *t.* At t=575, the proportion of respondents who have not quit smoking is 0.56 (Figure 2.13 and Table 2.18). An estimated 56% of all smokers (who do not die) smoke for more than 48 years. An estimated 44% of smokers quit in 48 years or less. The confidence interval around the survivor function is wider towards the end of the distribution as the observed number of people at risk and of quitters in this range is small.

Figure 2.13: Kaplan–Meier survival estimates, full sample (Table 2.18 column 8)



An alternative way to present the hazard function is by calendar year (Figure 2.14). The hazards of smoking cessation and the price index decreased from 1970 to the late 1990s. Cigarette prices were lowest in 1988 (index of 0.27). From the 1990s, the price index and the hazard of quitting increased.

Figure 2.14: Cigarette price index (CPI tobacco/CPI all items) and smoking cessation rates from 1970 to 2017



Log-rank test for equality of survivor functions

The non-parametric log-rank test compares the observed and expected number of failures for each group at each failure time and combines these comparisons over all observed failure times (Stata Netcourse 631, 2019). The null hypothesis of the log-rank test is that the survivor functions of groups are the same

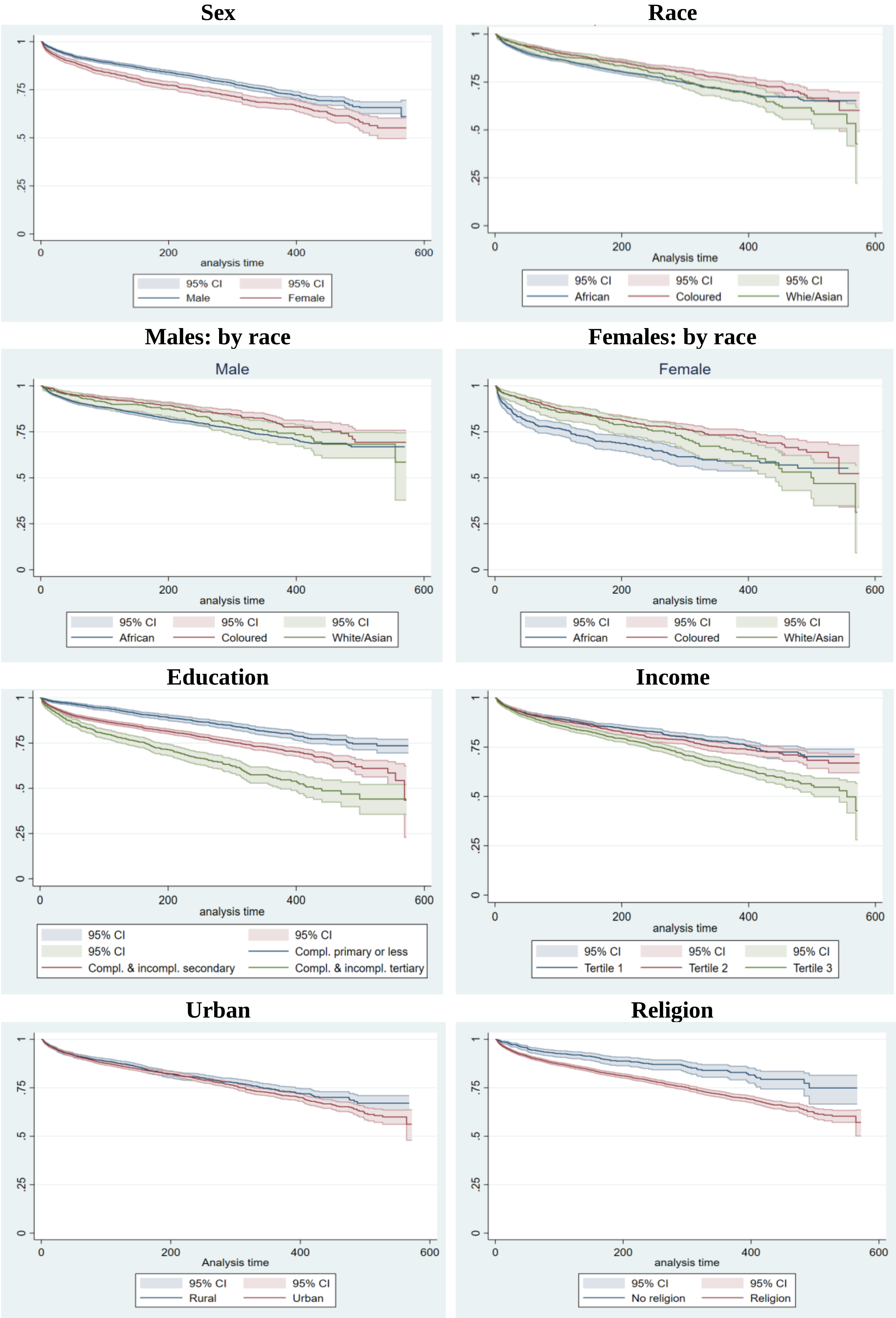
Table 2.19 shows log-rank tests for the variables used in the regression analysis. ‘Events observed’ (column 3) refers to the number of failures observed. For example, for the sex variable, 934 events were observed for males and 513 for females. ‘Events expected’ refers to the number of events that would be expected if males and females shared the same survivor function: 1045 failures for males and 402 failures for females. The observed events differed enough from the expected events to produce significant chi-squared values with p-values that are less than 0.005 for all variables except the *urban* variable (p=0.10). When the variables race and sex are interacted, the results indicate that males and females within population groups have significantly different survival functions.

Table 2.19: Log-rank test for equality of survivor functions

		Events observed	Events expected	chi2	Pr>chi2
Sex	Male	934	1045		
	Female	513	402		
	Total	1447	1447	42.38	*0.00*
Race	African	896	826		
	Coloured	379	456		
	White/Asian	172	165		
	Total	1447	1447	19.30	*0.00*
Race*sex	African male	709	786		
	African female	187	110		
	Total	896	896	61.89	*0.00*
Race*sex	Coloured male	147	189		
	Coloured female	232	190		
	Total	379	379	18.60	*0.00*
Race*sex	White/Asian male	78	98		
	White/Asian female	94	74		
	Total	172	172	9.06	*0.00*
Education	Complete primary or less (incl. no education)	299	480		
	Complete and incomplete secondary	841	791		
	Complete and incomplete tertiary	306	175		
	Total	1446	1446	171.89	*0.00*
Urban	Rural	439	468		
	Urban	1008	979		
	Total	1447	1447	2.73	*0.10*
Religion	No religion	118	203		
	Religion	1324	1239		
	Total	1442	1442	41.36	*0.00*
Income	Tertile 1	390	460		
	Tertile 2	450	488		
	Tertile 3	607	499	36.84	*0.00*
1995 TC regulations	Pre-1995	227	399		
	From 1995	1220	1048		
	Total	1447	1447	111.22	*0.00*
2001 TC regulations	Pre-2001	399	615		
	From 2001	1048	832		
	Total	1447	1447	142.85	*0.00*
Illicit trade	Pre-2010	862	1073		
	From 2010	585	374		
	Total	1447	1447	170.64	*0.00*

The results from Table 2.19 are depicted graphically with 95% confidence intervals (Figure 2.15).

Figure 2.15: Kaplan–Meier survival estimates



Regression results

Interpreting regression results: coefficients, odds ratios, or hazard ratios

Results can be presented as coefficients, odds ratios, or hazard ratios. An antilogged coefficient from a model with a logit link is an *odds ratio*, an antilogged coefficient from a model with a cloglog link is a *hazard ratio.* The cloglog specification, unlike the logit, has a response curve that is asymmetric (see the section 'Logit and cloglog models (non-parametric models)' in the methods section).

The easiest way to interpret the coefficient on the price/tax variable is to calculate the logarithm of price/tax before inserting the variable in the regressions. Forster & Jones (2001) used the natural logarithm of tax, while Kidd & Hopkins (2004) used the natural logarithm of price. These coefficients are read directly as the elasticity of tax/price.

A positive coefficient indicates that the risk of quitting increases for higher values of the covariate. For example, a coefficient on price of 0.8 indicates that a 1% increase in the price of cigarettes increases the hazard of quitting by 0.8%.

Odds or hazard ratios are a more intuitive way to assess the effects of categorical indicators. An odds or hazard ratio of 1 represents equivalence in the odds or hazard between groups. An odds or hazard of 1.5 on a categorical variable, such as sex (where male is the base), indicates that the odds or hazard rate of quitting for females is 1.5 times those of males. Put differently, females face an odds or hazard rate of quitting that is 50% greater than males. Odds and hazard ratios are a weighted average of the true hazard ratios over the entire follow-up period. For example, the overall hazard ratio of 1.5 is a weighted average of the time-varying hazard ratios, which could close to 2 in the first months of follow-up and decline to 1 later.

Results by sex or full sample?

Since smoking patterns often differ substantially by sex, it may be necessary to evaluate the determinants of smoking cessation separately for male and female ever-smokers. If patterns are similar, then the split is unnecessary. Table 2.20 shows the coefficients and hazard ratios of a fully specified Cox proportional hazards model. Regressions 1 and 2 are for the full sample, regressions 3 and 4 are for males, and regressions 5 and 6 are for females. Regressions 1, 3, and 5 show the coefficients, while regressions 2, 4, and 6 show the hazard ratios. The full sample consists of 1 448 972 observations from 7657 ever-smokers. The male sample consists of 1 039 172 observations from 5609 ever-smokers, and the female sample consists of 409 800 observations from 2048 ever-smokers.

The results split by sex are all in the same direction and of similar magnitude to those of the full sample. The price coefficient for the full sample is 0.54, which indicates that a 1% increase in the price of cigarettes increases the hazard of smoking cessation by 0.54%. Males and females do not have statistically different price elasticities (males 0.55, 95% CI: 0.31−0.80; females 0.53, 95% CI: 0.21−0.86).

Table 2.20: Cox proportional hazards model for the full sample, and by sex

	Full sample		Males		Females	
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	coefficient	hazard ratio	coefficient	hazard ratio	coefficient	hazard ratio
Ln (Real cigarette price index)	0.54***	1.72***	0.55***	1.74***	0.53***	1.71***
	(0.10)	(0.17)	(0.12)	(0.22)	(0.17)	(0.28)
Male	**0.00**	**1.00**				
Female	0.60***	1.83***				
	(0.06)	(0.12)				
African	**0.00**	**1.00**	**0.00**	**1.00**	**0.00**	**1.00**
Coloured	-0.54***	0.58***	-0.46***	0.63***	-0.70***	0.50***
	(0.07)	(0.04)	(0.10)	(0.06)	(0.10)	(0.05)
White/Asian	-0.55***	0.58***	-0.36***	0.70***	-0.88***	0.42***
	(0.10)	(0.06)	(0.13)	(0.09)	(0.15)	(0.06)
Rural	**0.00**	**1.00**	**0.00**	**1.00**	**0.00**	**1.00**
Urban	-0.06	0.94	-0.05	0.95	-0.11	0.89
	(0.06)	(0.06)	(0.07)	(0.07)	(0.13)	(0.11)
Complete and incomplete primary (incl. no edu)	**0.00**	**1.00**	**0.00**	**1.00**	**0.00**	**1.00**
Complete and incomplete secondary	0.36***	1.44***	0.28***	1.32***	0.53***	1.69***
	(0.08)	(0.11)	(0.09)	(0.12)	(0.13)	(0.22)
Complete and incomplete tertiary	0.86***	2.35***	0.75***	2.12***	1.03***	2.80***
	(0.10)	(0.23)	(0.12)	(0.26)	(0.17)	(0.47)
Income tertile 1	**0.00**	**1.00**	**0.00**	**1.00**	**0.00**	**1.00**
Income tertile 2	0.10	1.11	0.13	1.14	0.07	1.07
	(0.07)	(0.08)	(0.09)	(0.10)	(0.12)	(0.13)
Income tertile 3	0.26***	1.30***	0.21**	1.23**	0.40***	1.49***
	(0.08)	(0.10)	(0.09)	(0.11)	(0.13)	(0.20)
No religion	**0.00**	**1.00**	**0.00**	**1.00**	**0.00**	**1.00**
Religion	0.56***	1.75***	0.55***	1.74***	0.58**	1.78**
	(0.10)	(0.17)	(0.11)	(0.19)	(0.25)	(0.44)
1995 TC regulations	0.18	1.20	0.29	1.34	-0.04	0.96
	(0.20)	(0.24)	(0.24)	(0.32)	(0.34)	(0.33)
2001 TC regulations	-0.50**	0.61**	-0.58**	0.56**	-0.36	0.70
	(0.20)	(0.12)	(0.25)	(0.14)	(0.32)	(0.22)
Illicit trade	0.02***	1.02***	0.02***	1.02***	0.02***	1.02***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Individuals (ever-smokers)	7657	7657	5609	5609	2048	2048
Observations	1,448,972	1,448,972	1,039,172	1,039,172	409,800	409,800

Standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

More formally, a Likelihood Ratio (LR) test of the models using the interactions approach indicates that the full sample is preferred to the sample split by sex. A LR test of the null hypothesis that all male and female slope coefficients are equal is not rejected with a Chi-squared statistic of 16.27 (p = 0.179). Further analysis is therefore done on the full sample. Although Table 2.20 shows that there is no difference in the price elasticity between men and women, I present an alternative way of investigating sex differentials (interacting with the price variable with sex) (Table 2.24). In a separate regression, the price variable is interacted with race to investigate whether or not the price elasticity varies by race (Table 2.24).

Building the model

Since hazard ratios (i.e., the exponential of the coefficient) are a more intuitive way to assess the effects of categorical indicators, and most variables are categorical, only hazard ratios are reported in Table 2.21 (except price, for which coefficients are also reported).

Regression 1 accounts for price only; regression 2 includes demographic indicators (sex and population group); regression 3 includes SES indicators (urban, education, and income); regression 4 includes religion; regression 5 includes the 1995 and 2001 tobacco control regulations; regression 6 is the same as regression 5 but without price (to test whether the tobacco control variables would be significant in the absence of the price measure); regression 7 includes an indicator for illicit trade; regression 8 is the same as regression 7 but excludes the price indicator.

Regressions 1 and 2 report results from 7687 unique individuals. There are fewer individuals in regression 3 (n=7672) as some educational information from 15 individuals was missing. Information on religion from 15 individuals was missing, reducing regressions 4 to 8 to n=7657. Each regression consists of approximately 1.45 million observations (see Table 2.1).

Table 2.21: cloglog model (results reported as hazard ratios), duration dependency accounted for using a smooth polynomial

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln (Real cigarette price index)	2.33***	2.37***	2.08***	2.08***	2.34***		1.73***	
	(0.15)	(0.15)	(0.14)	(0.14)	(0.18)		(0.17)	
Coefficient	*0.85****	*0.86****	*0.73****	*0.73****	*0.85****		*0.55****	
	(0.06)	*(0.06)*	*(0.07)*	*(0.07)*	*(0.07)*		*(0.10)*	
Male		**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**
Female		1.77***	1.91***	1.84***	1.84***	1.86***	1.83***	1.83***
		(0.11)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
African		**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**
Coloured		0.64***	0.60***	0.56***	0.58***	0.55***	0.58***	0.57***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
White/Asian		0.92	0.57***	0.57***	0.57***	0.48***	0.58***	0.54***
		(0.08)	(0.06)	(0.06)	(0.06)	(0.05)	(0.06)	(0.05)
Rural			**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**
Urban			0.96	0.94	0.94	0.93	0.94	0.94
			(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Complete and incomplete primary (incl. no edu)			**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**
Complete and incomplete secondary			1.48***	1.46***	1.46***	1.85***	1.44***	1.54***
			(0.11)	(0.11)	(0.11)	(0.13)	(0.11)	(0.12)
Complete and incomplete tertiary			2.43***	2.38***	2.38***	3.03***	2.36***	2.55***
			(0.24)	(0.23)	(0.23)	(0.29)	(0.23)	(0.25)
Income tertile 1			**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**
Income tertile 2			1.13*	1.11	1.11	1.08	1.11	1.10
			(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Income tertile 3			1.33***	1.29***	1.29***	1.21**	1.30***	1.28***
			(0.10)	(0.10)	(0.10)	(0.09)	(0.10)	(0.10)
No religion				**1.00**	**1.00**	**1.00**	**1.00**	**1.00**
Religion				1.76***	1.76***	1.73***	1.75***	1.74***
				(0.17)	(0.17)	(0.17)	(0.17)	(0.17)
1995 TC regulations					1.05	1.53***	1.19	1.50**
					(0.21)	(0.23)	(0.23)	(0.25)
2001 TC regulations					0.52***	1.25*	0.60***	0.98
					(0.10)	(0.17)	(0.12)	(0.15)
Illicit trade							1.02***	1.04***
							(0.00)	(0.00)
Duration dependency (smooth polynomial)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Individuals (ever-smokers)	7687	7687	7672	7657	7657	7657	7657	7657
Observations	1 453 494	1 453 494	1 450 804	1 448 972	1 448 972	1 448 972	1 448 972	1 448 972

Standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

A coefficient of 0.85 (95% CI: 0.72−0.97) on the price variable indicates that a 1% increase in the real price of cigarettes increases the hazard of quitting by 0.85% (regression 1). The price coefficient does not change substantially when other variables are added (regressions 2−6).

In 1995 warning labels on tobacco packaging and advertising material were implemented. The 2001 legislation banned all tobacco advertising and sponsorship, prohibited smoking in all public spaces and workplaces, and prohibited the distribution of free cigarettes. One would expect that these policies would result in an increase in quitting (hazard ratios greater than 1). In regression 5, the 1995 variable is in the expected direction (although not significant), while the 2001 variable is in the unexpected direction (and significant at the 1% level). To test if price is dominating regression 5, price is excluded in regression 6. This results in both tobacco control variables being in the expected direction, and significant at the 1% and 10% level respectively.

Including the illicit trade variable as a covariate decreases the effectiveness of price on smoking cessation (a price elasticity of 0.55 (95% CI: 0.35−0.74) in regression 7 compared to 0.85 (95% CI: 0.70−1.00) in regression 5).

The hazard ratio on the illicit trade variable is 1.02 (95% CI: 1.01−1.03), which indicates that a 1 percentage point increase in illicit trade increases the hazard of quitting by 2%. This result is counterintuitive. One would expect that the presence of illicit cigarettes would result in fewer people quitting. However, the inclusion of the illicit trade variable does not affect the main conclusion that an increase in price results in an increase in smoking cessation. Regression 8 is the same as regression 7, but the price variable is omitted. The illicit trade hazard ratio increases to 1.04 (95% CI: 1.03−1.04).

Various tests were computed to establish which of the eight regressions in Table 2.21 provided the best statistical fit (Table 2.22). Since R-squared is an inadequate measure for the goodness-of-fit in nonlinear models (Spiess & Neumeyer, 2010), it is not reported. In the case of non-nested models, Akaike (1974) proposed penalizing each model's log likelihood to reflect the number of parameters being estimated and then comparing them.

Although the best-fitting model is the one with the largest log likelihood, the preferred model is the one with the best score based on the information criterion. In this case, the best fitting and the preferred model is regression 7 (AIC: 21 999; LR chi2: 842) (Table 2.22). Regression 7 is used to explain the results, and to compare the cloglog models to alternative specifications (Table 2.23).

Table 2.22: Log-likelihood values, LR Chi2, AIC and BIC from cloglog with quartic polynomial model

Regression	N	Log-Likelihood (Intercept Only)	Log-Likelihood (Full model)	df	LR chi2	AIC	BIC
1	1 453 494	-11 448	-11 180	5	536	22 371	22 432
2	1 453 494	-11 448	-11 130	8	637	22 275	22 373
3	1 450 804	-11 439	-11 050	13	778	22 126	22 284
4	1 448 972	-11 402	-10 999	14	806	22 026	**22 197**
5	1 448 972	-11 402	-10 992	16	820	22 017	22 212
6	1 448 972	-11 402	-11 060	15	685	22 150	22 333
7	1 448 972	-11 402	-10 981	17	**842**	**21 997**	22 203
8	1 448 972	-11 402	-10 997	16	811	22 026	22 221

Preferred specification (Table 2.21 regression 7)

A hazard rate of 1.83 (95% CI: 1.62−2.07) on the sex variable indicates that the hazard rate of quitting for females is 1.83 times the hazard rate for males. Put differently, females face a hazard of quitting that is about 80% greater than the hazard of quitting for males. Compared to Africans, Coloureds and Whites/Asians are all less likely to quit. The hazard rate for Coloureds is 0.58 (95% CI: 0.51−0.67) times that of Africans. There is no evidence that the probability of quitting differs for respondents living in rural areas than for those living in urban areas.

Higher education increases the likelihood of quitting. The hazard rate of respondents with complete and incomplete secondary schooling is 1.44 (95% CI: 1.24−1.67) times the hazard rate of the base category (respondents with up to complete primary education). The hazard rate of respondents with tertiary education (including incomplete tertiary education) is 2.36 (95% CI: 1.94−2.85) times that of the base category. The hazard rate of respondents in income tertile 2 is 1.11 (95% CI: 0.95−1.27) times the hazard rate of respondents in income tertile 1. The hazard rate of respondents in income tertile 3 is 1.30 (95% CI: 1.12−1.51) times the hazard rate of respondents in income tertile 1. The hazard rate of respondents affiliated to a religion is 1.75 (95% CI: 1.44−2.12) times the hazard rate of respondents with no religious affiliation.

Although regression 7 finds no evidence that the 1995 and 2001 legislation increased smoking cessation (hazard ratio of 1.19 (95% CI: 0.81−1.75) and 0.60 (95% CI: 0.41−0.88) respectively), this result is driven by the impact of price, which dominates the regression.

Choosing preferred model

Regression results from the Cox proportional hazards, logit, cloglog, Weibull, and split-population duration models are reported in Table 2.23. Duration dependency is built into the Weibull and Cox proportional hazards models, whereas duration dependency needed to be specified in the logit, cloglog, and split-population duration models. Although the split-population duration model may not make sense because everyone will quit smoking when they die, it was included here for the sake of completeness. In the split model, the distribution of time to quit is assumed to apply only to those people who will eventually quit. A regression was run to determine whether the event will occur and, conditional on the event occurring, the hazard over time was estimated.

Irrespective of the specifications, positive and statistically significant associations were found between cigarette prices and smoking cessation (Table 2.23).

Duration dependency (*duration* time, not *calendar* time) in the logit and cloglog models was accounted for in two ways: (1) time dummies (regressions 2 and 4), and (2) smooth polynomials (regressions 3 and 5).

The total number of observations in regression 2 (logit with dummies) and regression 4 (cloglog with dummies) is lower by 3156 observations than regression 3 (logit with polynomial) and regression 5 (cloglog with polynomial) because two time periods (D_{43} [n=2033] and D_{45} [n=1123]) were omitted from the regressions as there were no quitters in these time periods.

The split-population duration model was estimated using the smooth polynomial to account for duration time. The regression with dummy variables to account for duration time did not run (Stata error message 'could not calculate numerical derivatives flat or discontinuous region encountered'). The probability that smokers will never quit is 0.57, which corresponds with the earlier result that 56% of respondents smoke for more than 48 years after smoking onset (Figure 2.13: Kaplan−Meier survivor function, and Table 2.18: life table).

For the Weibull regression, Stata reported a Wald test for ln(p)=0. The test statistic (not shown in Table 2.23) is −16.13. We reject the null hypothesis that the hazard is constant (that it arose from a simple exponential distribution). This is equivalent to testing p=1 (see Figure 2.2) (Stata Netcourse 631, 2019).

Table 2.23: Regression results from different models

VARIABLES	STCOX HRs	LOGIT ORs	LOGIT ORs	CLOGLOG HRs	CLOGLOG HRs	WEIBULL HRs	SPSURV HRs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Ln (Real cigarette price index)	1.72***	1.73***	1.73***	1.73***	1.73***	1.76***	1.88***
	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.20)
Coefficient	*0.54****	*0.55****	*0.55****	*0.55****	*0.55****	*0.57****	*0.63****
	(0.10)	*(0.10)*	*(0.10)*	*(0.10)*	*(0.10)*	*(0.10)*	*(0.10)*
Male	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**
Female	1.83***	1.83***	1.83***	1.83***	1.83***	1.84***	2.13***
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.17)
African	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**
Coloured	0.58***	0.58***	0.58***	0.58***	0.58***	0.58***	0.49***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
White/Asian	0.58***	0.58***	0.58***	0.58***	0.58***	0.58***	0.47***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Rural	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**
Urban	0.94	0.94	0.94	0.94	0.94	0.94	0.91
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)
Complete and incomplete primary (incl. no edu)	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**
Complete and incomplete secondary	1.44***	1.44***	1.44***	1.44***	1.44***	1.43***	1.58***
	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)	(0.15)
Complete and incomplete tertiary	2.35***	2.36***	2.36***	2.35***	2.36***	2.32***	2.91***
	(0.23)	(0.23)	(0.23)	(0.23)	(0.23)	(0.22)	(0.37)
Income tertile 1	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**
Income tertile 2	1.11	1.11	1.11	1.12	1.11	1.11	1.18*
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.10)
Income tertile 3	1.30***	1.30***	1.30***	1.30***	1.30***	1.29***	1.36***
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.010)	(0.13)
No religion	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**
Religion	1.75***	1.75***	1.75***	1.75***	1.75***	1.75***	2.01***
	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.23)
1995 TC regulations	1.20	1.20	1.19	1.20	1.19	1.17	1.27
	(0.24)	(0.24)	(0.23)	(0.24)	(0.23)	(0.22)	(0.25)
2001 TC regulations	0.61**	0.61**	0.60***	0.61**	0.60***	0.61**	0.59***
	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)	(0.12)
Illicit trade	1.02***	1.02***	1.02***	1.02***	1.02***	1.02***	1.03***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
Duration dependency	Semi-parametric	Dummy variables	Smooth polynomial	Dummy variables	Smooth polynomial	Weibull	Smooth polynomial
Constant		0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Ln_p						-0.35***	
						(0.02)	
Cure_p							0.28*
							(0.15)
Prob (never quit)							0.57
Individuals (ever-smokers)	7657	7657	7657	7657	7657	7657	7657
Observations	1 448 972	1 445 816	1 448 972	1 445 816	1 448 972	1 448 972	1 448 972

Standard errors in parentheses

**** p<0.01, ** p<0.05, * p<0.1*

The results were extremely stable across models. Figure 2.11 shows that the hazard rate in each month is less than 0.007. Figure 2.8 and Table 15 shows that when the hazard probability is small (less than 0.2), both logit and cloglog transformed hazard probabilities yield similar values. It is therefore not surprising that the odds rations and hazard ratios are near identical.

Given the stability in the results, the final choice of the 'best' model was inconsequential. In line with Guindon, Paraje & Chaloupka (2019) and Guindon, Paraje & Chávez (2018), I used the cloglog model that accounts for duration dependency using a smooth polynomial (model 5) as the final model with interaction terms.

Adding sex and race interaction terms

Regression 1 in Table 2.24 shows the coefficients and hazard ratios according to Table 2.21 regression 7 (cloglog model with smooth polynomial). Sex and price were interacted in regression 2. The coefficient on the interaction term is 0.02 and is not significant, indicating that price elasticity is not statistically different between males and females, confirming results from Table 2.20. The price coefficient for males is 0.54 (95% CI: 0.33−0.75), and the price coefficient for females is 0.56 (95% CI: 0.32−0.81). Regression 3 presents results from interacting price and race. The coefficient for Africans is 0.59 (95% CI: 0.37−0.81), for Coloureds 0.44 (95% CI: 0.18−0.71), and for Whites/Asians 0.59 (95% CI: 0.24−0.93). The price elasticities across races are not statistically different. Although the results are not statistically different, they may suggest that Coloureds are less responsive to prices.

Table 2.24: Fully specified model (Table 2.21 regression) using a cloglog model with a smooth polynomial, with interaction terms

	(1) No interactions		(2) Sex#price interaction		(3) Race#price interaction	
VARIABLES	Coefficient	HR	Coefficient	HR	Coefficient	HR
Ln (Real cigarette price index)	0.55***	1.73***	0.54***	1.72***	0.59***	1.80***
	(0.10)	(0.17)	(0.11)	(0.19)	(0.11)	(0.20)
Male	**0.00**	**1.00**	**0.00**	**1.00**	**0.00**	**1.00**
Female	0.60***	1.83***	0.51	1.66	0.60***	1.83***
	(0.06)	(0.12)	(0.52)	(0.87)	(0.06)	(0.12)
African	**0.00**	**1.00**	**0.00**	**1.00**	**0.00**	**1.00**
Coloured	-0.55***	0.58***	-0.55***	0.58***	0.07	1.08
	(0.07)	(0.04)	(0.07)	(0.04)	(0.59)	(0.63)
White/Asian	-0.55***	0.58***	-0.55***	0.58***	-0.54	0.58
	(0.10)	(0.06)	(0.10)	(0.06)	(0.75)	(0.44)
Rural	**0.00**	**1.00**	**0.00**	**1.00**	**0.00**	**1.00**
Urban	-0.06	0.94	-0.06	0.94	-0.06	0.94
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Complete and incomplete primary (incl. no edu)	**0.00**	**1.00**	**0.00**	**1.00**	**0.00**	**1.00**
Complete and incomplete secondary	0.36***	1.44***	0.36***	1.44***	0.36***	1.43***

	(0.08)	(0.11)	(0.08)	(0.11)	(0.08)	(0.11)
Complete and incomplete tertiary	0.86***	2.35***	0.86***	2.35***	0.86***	2.36***
	(0.10)	(0.23)	(0.10)	(0.23)	(0.10)	(0.23)
Income tertile 1	**0.00**	**1.00**	**0.00**	**1.00**	**0.00**	**1.00**
Income tertile 2	0.10	1.11	0.10	1.11	0.10	1.11
	(0.07)	(0.08)	(0.07)	(0.08)	(0.07)	(0.08)
Income tertile 3	0.26***	1.30***	0.26***	1.30***	0.26***	1.30***
	(0.08)	(0.10)	(0.08)	(0.10)	(0.08)	(0.10)
No religion	**0.00**	**1.00**	**0.00**	**1.00**	**0.00**	**1.00**
Religion	0.56***	1.75***	0.56***	1.75***	0.56***	1.75***
	(0.10)	(0.17)	(0.10)	(0.17)	(0.10)	(0.17)
1995 TC regulations	0.18	1.19	0.18	1.19	0.18	1.19
	(0.20)	(0.23)	(0.20)	(0.23)	(0.20)	(0.23)
2001 TC regulations	-0.51***	0.60***	-0.51***	0.60***	-0.51***	0.60***
	(0.20)	(0.12)	(0.20)	(0.12)	(0.20)	(0.12)
Illicit trade	0.02***	1.02***	0.02***	1.02***	0.02***	1.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Duration dependency	-0.03***	0.97***	-0.03***	0.97***	-0.03***	0.97***
t	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
	0.00***	1.00***	0.00***	1.00***	0.00***	1.00***
t^2	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
	-0.00***	1.00***	-0.00***	1.00***	-0.00***	1.00***
t^3	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
	0.00***	1.00***	0.00***	1.00***	0.00***	1.00***
t^4	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Interactions						
Sex#Cigarette prices (in Ln)			**0.02**	1.02		
			(0.12)	(0.13)		
Coloured#c.Cigarette prices (in Ln)					**-0.15**	0.86
					(0.14)	(0.12)
White/Asian#c.Cigarette prices (in Ln)					**-0.00**	1.00
					(0.18)	(0.18)
Constant	-9.67***	0.00***	-9.03***	0.00***	-9.84***	0.00***
	(0.39)	(0.00)	(0.43)	(0.00)	(0.46)	(0.00)
Observations	1,448,972	1,448,972	1,448,972	1,448,972	1,448,972	1,448,972

Standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Own-price elasticities for cigarettes		
Sex: male	**0.54*** **	
	(0.11)	
Sex: female	**0.56*** **	
	(0.13)	
Population group: African		**0.59*** **
		(0.11)
Population group: Coloured		**0.44*** **
		(0.14)
Population group: White/Asian		**0.59*** **
		(0.18)

Proportional hazards assumption

The proportional hazards assumption of the Cox, logit, and cloglog models assumes that the survival curves for different groups are roughly parallel to each other (see Figure 2.1). Under this assumption, the shapes of the curves differ by a constant. A constant sex differential implies a stable discrepancy between males and females. A varying sex differential implies that the sex differential is larger in some periods than in others. If the proportional hazards assumption is invalid, parameter estimates may not be accurate. There are several statistical and graphical methods to check that the proportional hazards assumption is valid. Rather than treating any one of them as definitive, each method can be used as a piece of evidence. Passing one test does not necessarily mean that other tests will be passed (Stata Netcourse 631, 2019).

1. Interacting variables with time

To check the proportionality assumption, models can be extended to allow for covariate effects that vary freely with duration, by including interactions of covariates and duration time (Stata Netcourse 631, 2019). A time-dependent covariate that is significant indicates a violation of the proportionality assumption for that specific predictor.

The interacted variables that were significant were price, sex, race (Coloured), and illicit, indicating that the proportional hazards assumption for these variables was violated (Table 2.25). The overall test chi-squared statistic was 119.5 ($p<0.0001$), indicating that the model violates the proportional hazards assumption.

Table 2.25: Cox regression output including interactions with time

VARIABLES	Hazard ratio	Hazard ratio of variables interacted with time
Ln (Real cigarette price index)	2.14***	1.00***
	(0.31)	(0.00)
Sex (base: male)	2.27***	1.00***
	(0.20)	(0.00)
Coloured (base: African)	0.48***	1.00***
	(0.05)	(0.00)
White/Asian	0.49***	1.00
	(0.07)	(0.00)
Urban (base: rural)	0.88	1.00
	(0.08)	(0.00)
Complete and incomplete secondary (base: Complete and incomplete primary, incl. no edu)	1.60***	1.00
	(0.19)	(0.00)
Complete and incomplete tertiary	2.72***	1.00
	(0.39)	(0.00)
Income tertile 2 (base: tertile 1)	1.14	1.00
	(0.11)	(0.00)
Income tertile 3	1.24**	1.00
	(0.13)	(0.00)

Religion (base: no religion)	1.90***	1.00
	(0.26)	(0.00)
1995 TC regulations	0.88	1.00
	(0.29)	(0.00)
2001 TC regulations	0.58*	1.00
	(0.17)	(0.00)
Illicit trade	1.04***	1.00***
	(0.01)	(0.00)
Number of failures	1441	1441
Number of subjects	7657	7657
Observations	1,448,972	1,448,972

seEform in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: Stata code: `xi: stcox ln_cpi_100 gender i.race urban i.edu_1 i.INCOME religion tc_1995_decreasing_rate tc_2001_decreasing_rate illicit, tvc (gender race urban edu_1 INCOME religion tc_1995_decreasing_rate tc_2001_decreasing_rate illicit) texp(t)`

2. Test based on Schoenfeld residuals

Another method to test the proportionality assumption is to use the Schoenfeld and scaled Schoenfeld residuals (UCLA: Statistical Consulting Group). The null hypothesis is that the proportional hazards is met. The p-value of 0.000 for the global test in the output of Table 2.26 indicates that we would reject the null hypothesis indicating that the proportional hazards assumption is violated.

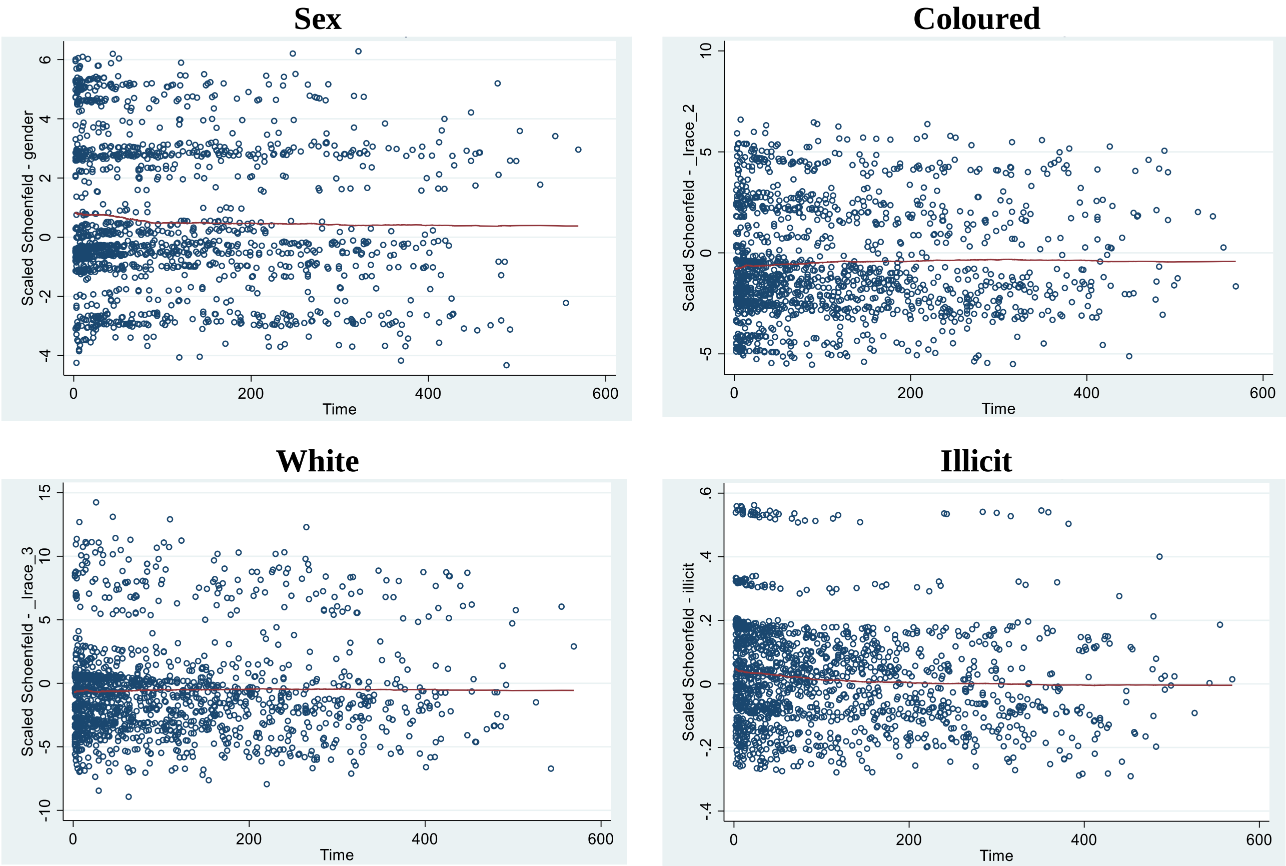
Table 2.26: Proportional hazards test

```
. estat phtest, det

      Test of proportional-hazards assumption

      Time:  Time
```

	rho	chi2	df	Prob>chi2
ln_cpi_100	-0.01196	0.21	1	0.6475
gender	-0.09855	14.96	1	0.0001
_Irace_2	0.07634	8.66	1	0.0032
_Irace_3	0.04313	2.72	1	0.0994
urban	0.02587	0.99	1	0.3199
_Iedu_1_1	-0.02968	1.27	1	0.2591
_Iedu_1_2	-0.03102	1.38	1	0.2402
_IINCOME_2	-0.00926	0.12	1	0.7242
_IINCOME_3	0.02372	0.79	1	0.3748
religion	-0.02480	0.88	1	0.3488
tc_1995_de~e	0.02933	1.18	1	0.2775
tc_2001_de~e	0.00662	0.06	1	0.8015
illicit	-0.13506	26.93	1	0.0000
global test		89.68	13	0.0000

Plots of variables that are significant in Table 2.26 at the 10% level (sex, Coloured, White, and illicit) are presented in Figure 2.16. In all cases, the lines are horizontal, indicating that the proportional hazards model is not violated, which contradicts the previous results.

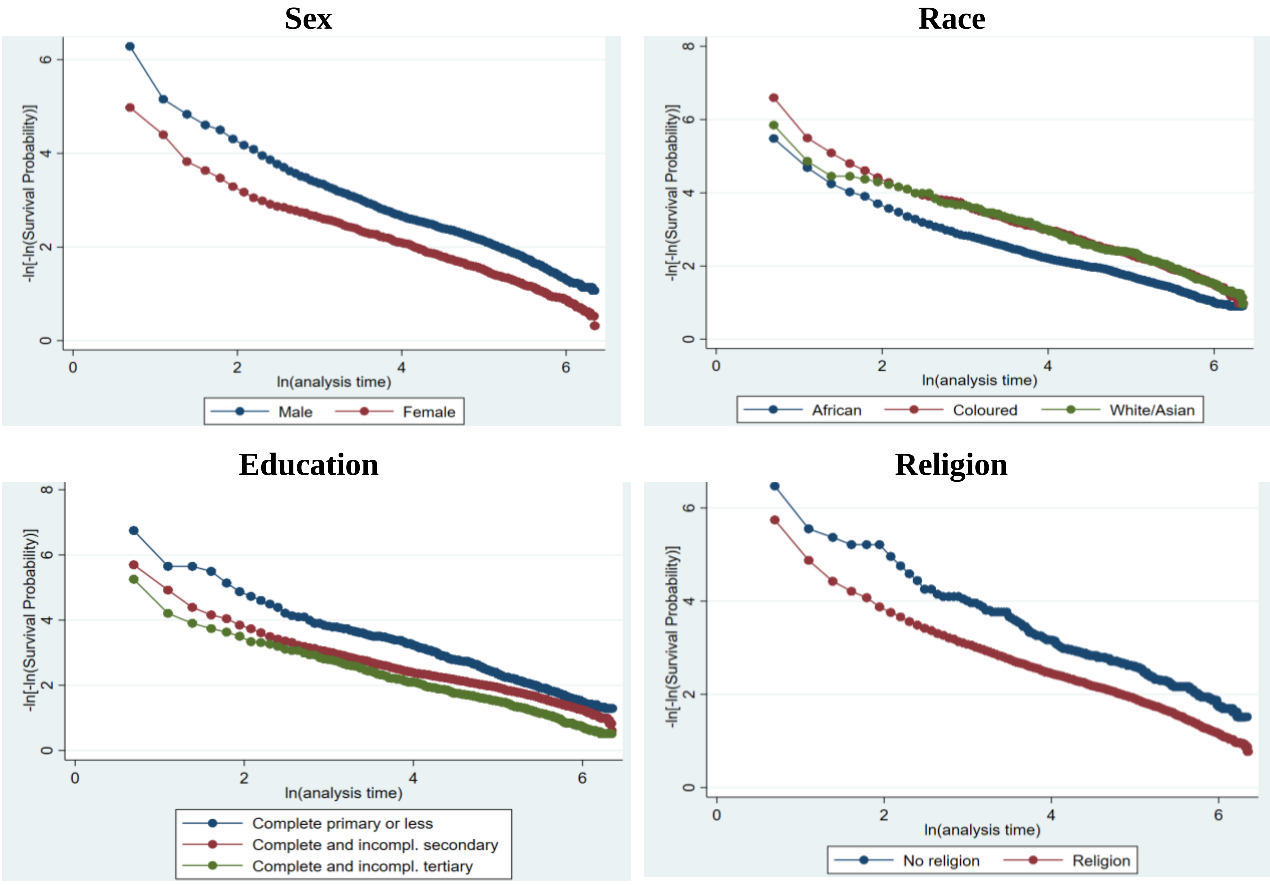
Figure 2.16: Scaled Schoenfeld residuals



3. Graphical methods

The proportional hazards assumption can also be assessed using graphical methods. These methods are intended for use with discrete covariates. The estimate –ln [(ln $S(t)$)] versus ln(t) is plotted for each level of the covariate, where $S(t)$ is the Kaplan−Meier survivor function (Stata Netcourse 631, 2019). Under the proportional hazard assumption, the curves should be parallel. An estimate of –ln [(ln $S(t)$)] is obtained using only the data for which the variable is equal to 0, another using only data for which the covariate is equal to 1, and so on. These separately estimated curves are plotted together on the same graph. If the proportional hazards assumption is true, these curves should be roughly parallel (Stata Netcourse 631, 2019). The graphs in Figure 2.17 show roughly parallel curves, indicating that the proportional hazards assumption is met.

Figure 2.17: Testing the proportionality assumption

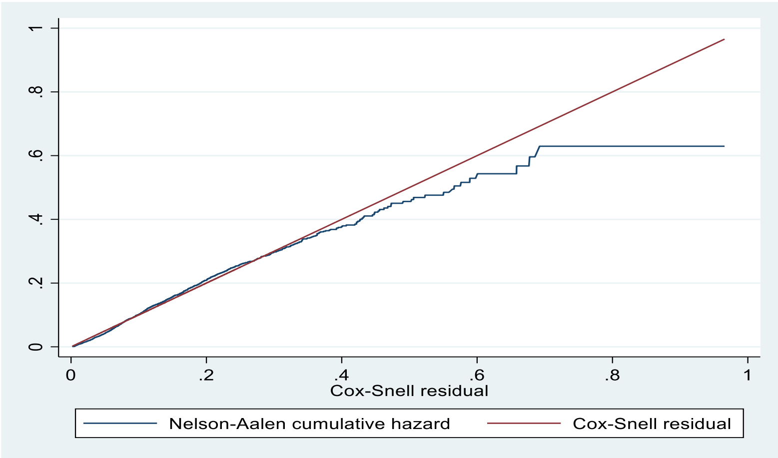


The results from the various tests do not provide a conclusive answer as to whether or not the proportional hazards assumption is met. This is not problematic as it is expected that the hazard ratio will vary over the follow-up period (Stensrud & Hernán, 2020).

Testing the overall fit of the model: Cox–Snell residuals

Following Forster & Jones (2001), Madden (2007), and López Nicolás (2002) (Table 2.3), Cox–Snell residuals were estimated to assess the overall fit of a model. If the Cox regression model fits the data, the Cox–Snell residuals have a standard censored exponential distribution with a hazard ratio of 1 (StataCorp). This statement holds only if the true parameters, β, and the true cumulative baseline hazard function, $H_0(t)$, are used in calculating the residuals. Because estimates $\hat{\beta}$ and $\hat{H}_0(t)$, are used, deviations from the 45° line could come in part from uncertainty about these estimates. Figure 2.18 shows a relatively well-fitted model with deviations in the right-hand tail, owing to a small sample through prior failures and censoring.

Figure 2.18: Cumulative Cox–Snell residuals



SENSITIVITY ANALYSIS

To test whether the results are robust to alternative specifications, four sensitivity analyses are conducted (Table 2.27, columns 2 to 5). Results from these models are compared to the main model, cloglog with polynomial, to account for duration dependency (Table 2.21 regression 7). For ease of reference, these results are repeated in Table 2.27 column 1.

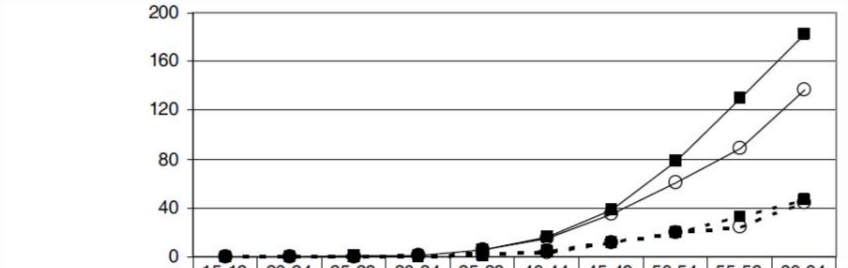
Sensitivity analysis 1: Informative censoring

Survival analysis rests on the assumption that censoring is non-informative. Younger individuals at the time of interview are less likely to have quit smoking and more likely to be censored. To test whether censoring affects the results, the sample is restricted to those who are 26 years or older at the time of interview. This cut-off is chosen because the median quit age in the full sample (n=7687) is 25 years. This reduces the sample to 4449 respondents.

Sensitivity analysis 2: Restrict sample to account for people who may have died from smoking-related diseases

People who have died from smoking-related diseases will not be in the risk set. This may result in a biased sample, since ever-smokers may be under-represented. To account for this, I drop respondents who are 50+ at the time of interview (age at which smokers start dying in relatively large numbers) (Anderson & Phillips, 2006). Figure 2.19 shows the age-specific death rates by sex from cancer of the lung, larynx and trachea in 1997 and 2004 (Anderson & Phillips, 2006). Death rates start to increase in the 50–54 age range. Dropping respondents who are 50+ reduced the sample to 6300 respondents.

Figure 2.19: Death rates by age and sex per 100 000 from cancer of the lung, trachea, and larynx: 1997 and 2004



	15-19	20-24	25-29	30-34	35-39	40-44	45-49	50-54	55-59	60-64
Male 1997	0.0	0.2	0.6	1.7	6.1	16.1	38.4	78.3	130.2	182.4
Male 2004	0.2	0.2	0.5	1.1	5.4	15.6	34.7	61.1	89.2	137.4
Female 1997	0.3	0.2	0.1	0.4	1.5	4.5	11.8	20.0	32.8	47.3
Female 2004	0.0	0.4	0.6	1.4	2.1	3.8	11.1	19.5	25.0	43.9

Source: Anderson, B. & Phillips, H. 2006. Adult mortality (age 15-64) based on death notification data in South Africa: 1997-2004. Pretoria: Statistics South Africa. Report No. 03-09-05.

Sensitivity analysis 3: Account for recent quitters who may relapse

To account for possible relapses, I excluded respondents whose age at interview minus the age at quitting is less than or equal to 1. Several studies have shown that relapse plateaus after about a year after quitting. Lancaster et al. (2006) reports that after initially successful quit attempts, many people return to smoking within a year. Similarly, García-Rodríguez et al. (2013) report that the first year after a quit attempt constitutes the period of highest risk for relapse. Dropping respondents who may have relapsed reduces the sample to 7541 respondents.

Sensitivity analysis 4: Keep respondents who started smoking before January 1970

In the main analysis, I dropped respondents who started smoking before January 1970 because I only have an index for monthly cigarette prices from January 1970. This removed 9% of the sample (786 of 8487 respondents). An alternative method is to follow respondents who began smoking before January 1970 **from** January 1970. 42 of these 786 respondents quit before 1970 and are therefore excluded. Including respondents who started smoking before January 1970 increases the sample to 8396 respondents.

Table 2.27: Sensitivity analyses

	Main model from Table 2.21, regression 7	**Sensitivity analysis 1**	**Sensitivity analysis 2**	**Sensitivity analysis 3**	**Sensitivity analysis 4**
	Exclude those who started smoking before 1970. Sample: Aged 15−91 at interview	Exclude younger people. Sample: Aged 26−91 at interview	Exclude older people. Sample: Aged 15−49 at interview	Exclude respondents who may relapse. Sample: Aged 15−91 at interview	Include those who started smoking before 1970. Sample: Aged 15−100 at interview
	(1)	(2)	(3)	(4)	(5)
VARIABLES	cloglog HRs	cloglog HRs	cloglog HRs	cloglog HRs	cloglog HRs
Ln (Real cig price index)	1.73***	1.58***	2.16***	2.06***	1.60***
	(0.17)	(0.17)	(0.27)	(0.21)	(0.15)
Coefficient	*0.55****	*0.46****	*0.77****	*0.72****	*0.47****
	(0.10)	*(0.11)*	*(0.13)*	*(0.10)*	*(0.09)*
Male	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**
Female	1.83***	1.72***	2.11***	1.87***	1.66***
	(0.12)	(0.12)	(0.16)	(0.13)	(0.09)
African	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**
Coloured	0.58***	0.61***	0.54***	0.58***	0.62***
	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)
White/Asian	0.58***	0.55***	0.60***	0.54***	0.66***
	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)
Rural	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**
Urban	0.94	0.92	0.90	0.88*	0.96
	(0.06)	(0.07)	(0.07)	(0.06)	(0.06)
Complete and incomplete primary (incl. no edu)	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**
Complete and incomplete secondary	1.44***	1.35***	1.54***	1.51***	1.46***
	(0.11)	(0.11)	(0.16)	(0.12)	(0.10)
Complete and incomplete tertiary	2.36***	2.38***	2.52***	2.67***	2.33***
	(0.23)	(0.26)	(0.31)	(0.28)	(0.21)
Income tertile 1	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**
Income tertile 2	1.11	1.18**	1.13	1.17**	1.07
	(0.08)	(0.10)	(0.09)	(0.09)	(0.07)
Income tertile 3	1.30***	1.51***	1.27***	1.34***	1.32***
	(0.10)	(0.14)	(0.11)	(0.11)	(0.09)
No religion	**1.00**	**1.00**	**1.00**	**1.00**	**1.00**
Religion	1.75***	1.76***	1.66***	1.77***	1.68***
	(0.17)	(0.20)	(0.18)	(0.19)	(0.15)
1995 TC regulations	1.19	1.12	0.75	1.07	1.14
	(0.23)	(0.22)	(0.23)	(0.21)	(0.20)
2001 TC regulations	0.60***	0.67**	0.64**	0.60***	0.67**
	(0.12)	(0.13)	(0.15)	(0.12)	(0.12)
Illicit trade	1.02***	1.00	1.02***	0.99***	1.02***
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)
Duration dependency	Smooth polynomial	Smooth polynomial	Smooth polynomial	Smooth polynomial	Smooth polynomial
Constant	0.00***	0.00***	0.00***	0.00***	0.00***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Individuals (ever-smokers)	7657	5 664	6 300	7460	8396
Observations	1 448 972	1 337 532	943 574	1 426 716	1 780 634

Standard errors in parentheses
**** p<0.01, ** p<0.05, * p<0.1*

Compared to the main model (Table 2.27 column 1), the results from the four sensitivity analyses (Table 2.27 columns 2−5) are robust. The illicit trade variable is no longer significant in sensitivity analyses 2 and 4. Only small changes are evident in the price coefficient in all four sensitivity analyses.

For sensitivity analysis 1 (Table 2.27 column 2: respondents aged 26−91 at interview), the price coefficient is slightly lower: 0.46 (95% CI: 0.24−0.67) compared to 0.55 (95% CI: 0.35−0.74). This indicates that censoring does not seem to be problematic.

For sensitivity analysis 2 (Table 2.27 column 3: respondents aged 15−49 at interview), the price coefficient is higher: 0.77 (95% CI: 0.52−1.02) compared to 0.55 (95% CI: 0.35−0.74). The results from sensitivity analysis 1 and 2 indicate that younger respondents may be more price-sensitive than older ones.

The price coefficient also increases in sensitivity analysis 3 (Table 2.27 column 4: respondents aged 15−91 at interview, recent quitters dropped), from 0.55 to 0.72 (95% CI: 0.52−0.92).

The results from sensitivity analysis 4 (Table 2.27 column 5: respondents aged 15−100 at interview) provide further evidence that older respondents may be less price-sensitive as the price coefficient decreases from 0.55 to 0.47 (95% CI: 0.29−0.65). This is supported by the existing literature (Gallet & List, 2003). Gallet & List (2003) systematically reviewed 86 different studies published up to 2001. They found greater responsiveness among younger people, with an average price elasticity of –1.43 for teenagers, –0.76 for young adults, and –0.32 for adults.

DISCUSSION

Using survival analysis techniques, I estimated that 56% of all ever-smokers smoke for more than 48 years. An estimated 44% of ever-smokers quit in 48 years or less. Females are more likely to quit than males. Depending on which variables are included in the regressions, the coefficient on the price variable ranged from 0.55 to 0.86, implying that a 10% increase in the price of cigarettes results in a 5.5% to 8.6% increase in the probability of quitting. The price elasticity is higher (0.73 to 0.86) when the illicit trade variable is excluded in the models (Table 2.21 regressions 1−5).

Given that illicit trade has reshaped the cigarette market since 2010, a variable to control for illicit trade is included in the preferred model. The fully specified cloglog model is tested against various other model specifications (logit, Cox proportional hazards, Weibull, and split-population duration models). The results from the models that include all variables are extremely robust. The price elasticity obtained from these models ranges from 0.54 to 0.63.

These results are consistent with various existing studies. Tauras & Chaloupka (1999) and Tauras (1999) found that prices are a significant determinant of smoking cessation. Both studies used a sample of US high school seniors at first interview, who were tracked for up to fourteen years. Tauras (1999) found a lower price elasticity than the current paper does: a 10% increase in the real price of cigarettes increased the probability of cessation among young adults by approximately 3.4% to 3.5%.

Tauras & Chaloupka (1999) found that females have a higher price elasticity than males. They found that a 10% increase in the real price of cigarettes increased the probability of smoking cessation by approximately 12% for young men and by 19% for young women. Ross et al. (2014), who used excise taxes instead of prices, found that a 10% increase in excise tax increases the probability of smoking cessation by 1.6 to 2.3% in Poland, Russia, and Ukraine.

My results differ from those of Kostova, Husain & Chaloupka (2017) and Kenkel, Lillard & Liu (2009) who did not find evidence that higher prices impact smoking cessation in China. Similarly, Kidd & Hopkins (2004), using data on the Australian population, found no evidence that prices impact the decision to quit.

Few studies, aside from Tauras & Chaloupka (1999), report elasticities for males and females separately. Forster & Jones (2001) found that excise taxes had an impact on smoking cessation for men but not for women. This is similar to results on smoking *onset* in South Africa. Using three waves of the NIDS data, Vellios & Van Walbeek (2016) found that price elasticities in the onset analysis were significant for males, but not for females. The current paper finds that despite a large gender disparity in smoking cessation (females quit at a rate that is about 1.8 times higher than that of males), both males and females in South Africa have the same price elasticity, which is highly significant for both males and females.

African females are more likely to quit smoking than Coloured and White/Asian females. The same is true for African males, but to a lesser degree. The price elasticities of these groups are not statistically different. Although the results are not statistically different, they may suggest that Coloureds are less responsive to prices.

Furthermore, I find a positive gradient between education and smoking cessation. Respondents with higher education are more likely to quit compared to those with less education. Those with complete and incomplete secondary education are more likely to quit than those with primary education or less. The effect is more distinct for respondents with complete or incomplete tertiary education. These results are consistent with the existing literature (Douglas, 1998; Forster & Jones, 2001; Kidd & Hopkins, 2004; Kostova, Chaloupka & Shang, 2015; Peretti-Watel, 2004; Ross et al., 2014). However, they differ from Kostova, Husain & Chaloupka (2017) who found no evidence that education is associated with the probability of quitting.

Given the strong correlation between income and education, it is not surprising that those with higher income were more likely to quit than those with lower income. Individuals in the highest income bracket (tertile 3) were more likely to quit than those in tertile 1. There is no statistical difference in quitting between individuals in income tertiles 2 and 3. Douglas (1998) found, similarly to this study, that family income has a statistically significant positive association with quitting. Kenkel, Lillard & Liu (2009) also found that wealthier men (quartile 4 versus quartile 1) were more likely to quit. On the other hand, Tauras & Chaloupka (1999) found no evidence that income impacts the probability of cessation for either males or females.

The results in the current paper indicate that respondents who practice a religion are more likely to quit than those who do not have any religious affiliation. Tauras & Chaloupka (1999) and Tauras (1999), the only other authors to investigate this variable, found that both males and females who participate in religious services were more likely to quit smoking than individuals with less religious attachment, which agrees with my results.

The results from the 1995 and 2001 tobacco control regulations produced mixed results. This may be because prices are the most effective tobacco control policy, therefore price may dampen the effect of these variables. If price is omitted from the regression, both variables become significant (the 1995 variable at the 1% level, and the 2001 variable at the 10% level), and indicate that stronger tobacco control legislation is associated with a higher probability of quitting.

Few authors control for other tobacco control variables than tax or price. López Nicolás (2002) included dummy variables to capture the effects of a ban advertising campaigns (1984) and a ban on smoking in public transport and improvements in health warnings (1992). He found that the advertising campaigns did not have a significant effect, but the health warnings were associated with a reduction in smoking duration.

Tauras (1999) and Tauras & Chaloupka (1999) included indicators reflecting state-level restrictions on smoking in private workplaces, restaurants, and other public places. In both papers the results are mixed. Tauras & Chaloupka (1999) found that state-level policies restricting smoking in private workplaces have a positive impact on the probability of cessation among employed young adult females.

Other restrictions on smoking in public places had little impact on female smoking-cessation decisions. Laws restricting smoking in private workplaces and public places had no significant impact on young adult male smoking-cessation decisions. Tauras (1999) found that policies restricting smoking in private workplaces and public places have a positive impact on smoking cessation in all of the models when regional fixed effects are not controlled for. Restaurant restrictions did not have a significant impact on young adult smoking-cessation decisions.

The results on the illicit trade variable are in the unexpected direction, indicating that an increase in illicit trade results in an increase in quitting. It is possible that this variable is estimating something other than illicit trade. I investigated per capita GDP, but it was stable over the period when illicit trade was increasing (from 2010 to 2017). I also investigated unemployment. The period post-2010 is characterised by increasing unemployment. One could argue that when smokers have less money they smoke less or quit. One could also argue that unemployment leads to depression and boredom, so that people smoke more. Given the high degree of speculation, I am unable to clarify why the coefficient on the illicit trade variable is in the unexpected direction.

The tobacco control policy response to these results is discussed in the concluding chapter. In summary, to reduce smoking prevalence effectively, the government should continue to increase excise taxes and concurrently address illicit trade.

Limitations

NIDS respondents were asked: ‘Do you smoke cigarettes?’ and ‘Did you ever smoke cigarettes regularly?’ Since smoking frequency is not specifically defined in the NIDS questionnaire (e.g., every day, at least three days a week, at least every week), smoking frequency is open to interpretation by respondents, resulting in some measurement error. For example, someone who experimented with smoking (e.g., smoked once a week at a nightclub) may say that they started smoking at age 15 and stopped smoking at age 16. Another person with the same smoking behaviour may answer ‘no’ to both questions.

There is likely to be recall bias amongst respondents about their age of onset and cessation. Smokers in the NIDS sample were asked ‘How old were you when you first smoked cigarettes?’ and ‘How old were you when you last smoked cigarettes regularly?’ People forget the precise age they started and quit smoking. For example, a person may say that he started smoking around age 20, when in fact he started at age 17. He may say he quit at age 50 when in fact he quit at age 55. Heaping around common values can result in a mismatch between the price variable and the dependent variable, smoking cessation.

Tauras & Chaloupka (1999) noted that recall bias by participants can introduce substantial measurement errors. This is especially problematic when respondents are asked to recall the exact year or age at which they initiated smoking when such events occurred decades earlier (Guindon, 2014).

The nature of the data limited the ability to include more time-varying individual and household-level covariates. For example, I was unable to use a time-varying measure of household income. Although education is a time-varying covariate, I used a time-invariant measure of education (highest level achieved). While a time-invariant variable for education is problematic for smoking onset, it is less problematic for the quitting analysis, as most ever-smokers who quit do so after they have achieved their highest level of education.

It is possible that some individuals may have changed their country of residence during the observation period, which I was unable to control for. In addition, I was unable to control for people moving between urban and rural areas. Given the migration towards cities in the past few decades, it is likely that many people moved from rural to urban areas.

During data cleaning, 1370 respondents were dropped. Respondents who changed their onset and quit age answers drastically between waves were deleted. Although this was a substantial portion of the sample, the remaining data are much cleaner.

I assumed that all heterogeneity is observed and attributable to the predictors included in the models. If the models omit one or more important predictors, there will be unobserved heterogeneity. If unobserved heterogeneity exists, the observed pattern of risk may not reflect the true pattern of risk (Singer & Willett, 2003).

CONCLUSION

Given that 56% of ever-smokers who do not die prematurely use cigarettes for more than 48 years, tobacco control measures to reduce smoking onset and increase smoking cessation seem justified. These measures are outlined in Articles 6 to 14 in the WHO's Framework Convention on Tobacco Control (World Health Organization, 2003).

Increasing excise taxes has been shown to be the most effective measure to reduce the demand for tobacco (International Agency for Research on Cancer, 2011). Higher cigarette excise taxes, which lead to higher retail prices, reduce smoking prevalence by encouraging smokers to quit. South Africa should continue to increase the price of cigarettes through excise tax increase. Further increases in the excise tax on cigarettes are likely to discourage the smoking habit and to hasten cessation for those who have already started.

However, if consumers are able to buy cheaper illicit cigarettes, the impact of price increases is likely to be reduced. The South African government should therefore implement measures to reduce the illicit trade in cigarettes, as outlined by the WHO’s Protocol to Reduce Illicit Trade (World Health Organization, 2013), while it concurrently increases excise taxes.

Other measures to increase smoking cessation include plain packaging for cigarette packs, where cigarette packs are stripped of all branding, and images of the health effects of smoking are printed on the packs. This is the topic of the next chapter.

CHAPTER 3: The impact of cigarette packaging and price on UCT students' smoking behaviour

INTRODUCTION

Plain packaging restricts the industry's use of the cigarette package as a promotional vehicle, reducing the appeal of cigarettes. Plain packaging, also referred to as standardised packaging, is a low-cost way to communicate the health risks of tobacco use. In countries where plain packaging laws have been implemented, cigarette manufacturers are required to remove all branding, including colours, images, corporate logos, and trademarks. Manufacturers can only print, on a dull background, the brand name in a standard size, font, and position on the pack. In 2012, Australia became the first country to require the plain packaging of tobacco products. Since then, 21 countries have followed their lead (Cunningham, 2022).

Plain packaging is proposed for South Africa in the draft Control of Tobacco Products and Electronic Delivery Systems Bill (CTPENDS) (Republic of South Africa: Department of Health, 9 May 2018). To assess the effectiveness of this policy, I evaluated how people react to plain packs with graphic health warnings (GHW) compared to the current pack, which is branded and has only a written health warning.

For plain packaging to be effective, consumers need to see the pack. In South Africa, many smokers do not see the pack because cigarettes are often sold as single sticks, despite the sale of singles being illegal. The Tobacco Control Amendment Act of 1999 states that '*No person shall sell or import for subsequent sale any prescribed tobacco product, unless—(a) such product is in a package*' (Republic of South Africa, 1999). Single sticks are not sold in any package. Despite the existence of legislation to prevent this, the law is not enforced, and the sale of single cigarettes is ubiquitous throughout South Africa. Van der Zee, Van Walbeek & Magadla (2019), using nationally representative data from 2017, found that approximately one-third of smokers in South Africa bought cigarettes as single sticks. If a third of smokers do not see plain packs, the effect of plain packaging will be diluted. By printing warnings on individual sticks, smokers who buy single sticks will at least see a written health warning.

To assess whether plain packaging would be effective in South Africa, I used a discrete choice experiment (DCE) to elicit preferences. Eliciting preferences can be done using two approaches: (1) 'revealed preference', where people's actions are observed in real markets, or (2) 'stated preference', where people are asked to state their preferences in hypothetical markets (Ryan, Gerard & Amaya-Amaya, 2008). DCEs fall under the second approach.

In the DCE, I also evaluated the impact of prices and warnings on individual sticks. Higher cigarette prices reduce demand for cigarettes (International Agency for Research on Cancer, 2011). A warning on each cigarette is thought to prolong the health message, as it would be visible when a cigarette is taken out a pack, making it more difficult to avoid. No country has yet (May 2022) implemented this tobacco control instrument. Canada was the first country to consider implementing individual cigarette stick warnings (Flanangan, 30 October 2018). On 10 June 2022, the government of Canada formally proposed the introduction of written health warnings printed on individual cigarettes (Government of Canada: Health Canada, 10 June 2022). A private member's bill was introduced in the UK parliament in June 2021, with its second reading in May 2022 (UK Parliament, 14 June 2021). To date (October 2022), the UK bill is still in the second reading phase.

Although there is sufficient international evidence that plain packaging reduces cigarette consumption (Drovandi et al., 2019c; Moodie C et al., 2012), South African policymakers require local, empirical research. In the South African context, Senkubuge (2020) evaluated the effectiveness of text-based health warning messages and GHWs on branded and plain packs. Participants were shown GHWs on branded packs and plain packs (one pack shown at a time). Using results from a ranking exercise, Senkubuge (2020) found that the most effective warning was lung cancer on the plain pack. Other effective health warnings were gangrene, impotence, abortion, and oral disease. Participants in the current study were shown branded and plain packs at the same time using a discrete choice experiment.

Discrete choice experiments (DCEs)

DCEs are also referred to as stated-choice models or choice-based conjoint analysis (Regmi et al., 2018). DCEs involve presenting respondents with a series of hypothetical scenarios (choice sets) consisting of two or more competing alternatives that vary in terms of several attributes (e.g., packaging or price). Most commonly, each respondent faces several choice questions within a single survey. For each choice set, respondents are asked to choose their preferred scenario. It is assumed that individuals will consider all information provided and then select the alternative with the highest utility (Ryan, Gerard & Amaya-Amaya, 2008).

The selection of a set of key attributes and their different values (referred to as 'levels', e.g., four price levels) is guided by the factors that are expected to affect respondents' choices. DCEs are designed to be as realistic as possible. This makes it necessary to customise experiments to reflect market conditions (Ryan, Gerard & Amaya-Amaya, 2008).

A full factorial design contains all possible combinations of the attribute levels. The advantage of a full factorial design is that all the effects of the attributes on choices can be investigated, i.e., parameter estimates can be obtained not only for the main effect on utility of each attribute individually but also for all the possible interactions between them. However, for most practical situations, the full factorial design is often very large and intractable, as it would be too costly and tedious to have participants consider all possible combinations (Ryan, Gerard & Amaya-Amaya, 2008). Even for a small factorial design, for example three attributes with four levels, there would be 4*4*4 = 64 combinations of attribute levels. For choice sets with two choices, there would be 2 016 unique choice sets (64*63/2). For this reason, researchers often select a subset (or fraction) of all possible combinations, known as a fractional factorial design (Ryan, Gerard & Amaya-Amaya, 2008).

Respondents' choices reveal which attributes are most or least important. Based on repeated observations of choices, researchers can examine how the various attributes affect the probability of choice (Vojáček & Pecáková, 2010).

DCEs have been used to measure a variety of choices. De Bekker-Grob, Ryan & Gerard (2012) reviewed 114 DCEs used in the health economics literature. Some examples include women's preferences for home versus hospital births, their preference for caesarean sections, depression treatment preferences, weight loss programs, chemotherapy treatment, and smoking cessation behaviour.

The literature review that follows first provides a background on DCEs, and then provides a summary of published papers that used DCEs to evaluate cigarette packaging. The existing literature on individual stick warnings and on the use of auctions to elicit willingness to pay for cigarettes is also covered.

LITERATURE REVIEW

Discrete choice experiments

Discrete choice modelling aligns with Lancaster's Economic Theory of Value that explains how consumers evaluate the costs and benefits of competing products to form overall impressions and make choices (Lancaster, 1966). In Lancaster's framework, it is assumed that these attribute levels determine the value (utility) of each alternative. Drawing on Lancaster's economic theory of value (Lancaster, 1966), DCEs assume that individuals derive utility from the underlying attributes of the commodity under valuation (rather than the commodity per se), and that individuals' preferences (as summarised by their utility function) are revealed through their choices.

Discrete choice modelling also complies with McFadden's Random Utility Theory, which proposes that utility is a latent construct that exists in consumers' minds and cannot be observed directly (McFadden, 1974). Random Utility Theory assumes a utility-maximising principle where consumers make trade-offs when making decisions and will choose alternatives that provide the greatest welfare. Utility is determined by how much importance customers place on a product's characteristics. The objective of a DCE is to identify which attributes are important in determining utility and how these attributes interact (Ryan, Gerard & Amaya-Amaya, 2008).

The most widely-used discrete choice model is McFadden's conditional logit model (McFadden, 1974). If a choice set included only two alternatives (i.e., where a respondent is asked to choose between alternatives A and B), binary choice models (e.g., logit or probit) are appropriate (Ryan, Gerard & Amaya-Amaya, 2008). More recently, studies ask respondents to choose between more than two alternatives, hence the conditional logit model is increasingly used. Multinomial logit models, also used to model choices, are often used to describe models that relate choices to the *characteristics of the respondents* making the choices, whereas a conditional logit model relates choices to the *elements defining the alternatives* from which respondents choose (Hauber et al., 2016).

The theoretical underpinnings of DCEs contain many assumptions from standard economic theory of consumer behaviour, specifically that participants are rational decision makers who seek to maximise preferences (Ryan, Gerard & Amaya-Amaya, 2008). Discrete choice behaviour can be formulated as an optimisation problem, where the consumer selects a consumption bundle such that their benefit (utility) is maximised, subject to their budget constraints (Ryan, Gerard & Amaya-Amaya, 2008).

Regmi et al. (2018) conducted a systematic review of papers that applied DCE methods, published in the tobacco control literature from 2000 to 2016. The authors focused on smoking cessation behaviour, anti-smoking policies, and preferences for smoking-cessation aids. Of the 12 papers analysed by Regmi et al. (2018), half of the studies focused on smoking cessation, two on smoking behaviour, two on electronic cigarette use, one on waterpipe smoking, and only one (Kotnowski et al., 2016) on cigarette packaging. The authors found that monetary attributes were the most influential in all studies.

It is unclear why several studies that fit the eligibility criteria were not included in Regmi et al. (2018), namely: (1) adult smokers aged ≥16 years, (2) economic evaluations, policy evaluations, preference measurements, and predictive epidemiological studies with choice-based response formats, and (3) studies using DCEs. It may be that the authors were focusing on cessation, but this criterion was not listed, and Kotnowski et al. (2016), which was included, did not focus on cessation. Other studies that fall into the evaluation time period, and that meet the criteria, include: Babineau & Clancy (2015), Bansal-Travers et al. (2011), Hammond et al. (2009), Hammond et al. (2014), Hammond & Parkinson (2009), and Rousu et al. (2014).

In total, I identified 11 relevant papers. The search was restricted to (1) studies that included cigarette packaging as an attribute, and (2) used a discrete choice experiment. Of those 11 papers, seven evaluated plain packaging: Barrientos-Gutierrez et al. (2021) (Mexico), Harris et al. (2017) (Uruguay), Kotnowski et al. (2016) (Canada), Babineau & Clancy (2015) (Ireland), Hammond et al. (2014) (UK), Bansal-Travers et al. (2011) (US), and Hammond et al. (2009) (UK). The remaining four papers evaluated packaging, but not plain packaging: Thrasher et al. (2022) (Mexico), Gendall et al. (2018) (New Zealand), Giang et al. (2016) (Vietnam), and Hammond & Parkinson (2009) (Canada). Of these eleven papers, only two, Kotnowski et al. (2016) and Giang et al. (2016), included price as an attribute.

The definition of ‘plain packaging’ has evolved over time. The term is now associated with the classic Australian pack, but plain packaging in initial research did not look like the Australian design. For example, in Bansal-Travers et al. (2011), the term plain packaging referred to a plain white pack with black text.

At least half of the papers used existing brands. Those that used fictitious brands include: Harris et al. (2017), Bansal-Travers et al. (2011), and Hammond & Parkinson (2009). It is unclear if Giang et al. (2016) and Gendall et al. (2018) used an existing or fictitious brand. Giang et al. (2016) did not mention a brand name, while Gendall et al. (2018) stated that they used an ‘unfamiliar’ brand name. Bansal-Travers et al. (2011) argued that existing brands could influence participants’ responses as they might feel a sense of brand loyalty when viewing the packs.

Five papers used conditional logit models (the focus of the remainder of the literature review). These were: Thrasher et al. (2022), Barrientos-Gutierrez et al. (2021), Harris et al. (2017), Giang et al. (2016), and Kotnowski et al. (2016). Looking at Babineau & Clancy (2015) allowed a further exploration of different methods used, such as chi-square tests (Babineau & Clancy, 2015; Bansal-Travers et al., 2011; Hammond & Parkinson, 2009; Hammond et al., 2009; Hammond et al., 2014) and GEE models (Babineau & Clancy, 2015; Hammond et al., 2014).

Thrasher et al. (2022) used a sample of 705 adult smokers. Although this paper is the most recent DCE on cigarette packaging, the authors did not consider plain packaging. This is surprising, given how international policy developments have moved towards the standard Australian design. Although not stated explicitly, it may be that the authors did not think the Australian design was the best to apply in the Mexican context, as they noted that research is needed to determine the most effective colour combination for GHWs, including whether the effects vary across socio-cultural contexts in which different colours can have different meanings (Spence, 2016; Thrasher et al., 2022). Instead of testing the classic Australian design, the authors tested whether switching the colour combination on current packs (black text on yellow background) would have a different effect from yellow text on a black background (Thrasher et al., 2022).

As well as colour combination, Thrasher et al. (2022) considered five other attributes: front-of-pack health warning size (30%, 75%), back-of-pack warnings (30% pictorial image, text only), brand (Marlboro, Pall Mall), brand variety (regular, flavour capsule), and health warning message (cancer, emphysema, blindness, gangrene). Using a sample of 705 Mexican smokers aged 18 to 50, the authors assessed willingness to buy, perceptions of which pack best informs about the dangers from smoking ('informative'), and motivation to quit. Respondents completed one of two blocks, each containing 16 choice sets. Each choice set consisted of two cigarette packs and an opt-out.

The authors found that the larger GHW size on the pack's front (75% rather than 30%) was associated with a lower willingness to buy a pack. Inclusion of a pictorial image on the back of the pack was also associated with a lower willingness to buy a pack. The GHW with black text and yellow background was perceived to be less informative, and giving less motivation to quit, than yellow text on a black background.

Also in Mexico, but considering plain packaging, Barrientos-Gutierrez et al. (2021) assessed plain packaging using a sample of 4325 respondents aged 12−14 years. Each respondent was randomised to evaluate one of six blocks that included eight choice sets. For each choice set of three packs (and an opt-out), participants were asked to select a pack in each set that: (1) is most/least attractive, (2) they are most/least interested in trying, and (3) is most/least harmful.

The experiment included six attributes: brand (Marlboro, Pall Mall, Camel), tobacco flavour (regular, menthol), flavour capsule (none, 1 capsule, 2 capsules), presence of descriptive terms (fine tobacco, aged tobacco, mild smell, flow filter), branding (branded, plain packaging), GHW size (30%, 75%), and GHW content (emphysema, mouth cancer).

The authors found that students perceived packs with larger GHWs as less attractive, less interesting to try, and more harmful than the current smaller GHW. The presence of flavour capsules and menthol-flavoured tobacco increased attractiveness and interest in trying, though perceptions of lower harm were found only for packs that included one flavour capsule. Packs with plain packaging and no descriptive terms were associated with lower attractiveness.

Harris et al. (2017) also evaluated plain packaging. The authors used a sample of 180 Uruguayan staff or students recruited at a university (all current smokers). Harris et al. (2017) considered risk only, which is limiting as it is difficult to link perceptions of risk with smoking cessation. Many smokers are aware of the risk of smoking but continue to smoke regardless, resulting in a difference between purchase decisions and risk decisions. The three attributes were: colour (white and blue, dark brown), warning (optimistic, negative), and packaging (three levels including plain packaging). Each participant was shown 11 choice sets. Participants were instructed to choose which of the two packs they considered to be less risky to health.

Harris et al. (2017) found that cigarettes in plain packaging were more likely to be perceived as posing higher health risk than packaging showing a brand or a modified brand. Using education as a proxy for socio-economic status (SES), the authors found no difference between respondents from different SES groups.

Giang et al. (2016), who did not consider plain packaging, used a sample of 5268 Vietnamese people aged 15 and older. The authors constructed eight blocks, each with eight choice questions and one repeated choice question. The authors considered four attributes: graphic type (text only and 4 GHWs), area covered (30%, 50%, and 85%), position (up, down), and cost (four price levels). The authors found that the text option was the most preferred and the image of lung cancer was the least preferred. Smokers preferred smaller GHWs to larger ones, the upper position to the lower position, and lower prices to higher prices.

Kotnowski et al. (2016), who considered plain packaging, sampled 448 female Canadian smokers and non-smokers aged 16–24 years. Respondents were shown 10 choice sets, each containing four packs with different combinations of the attributes, as well as an opt-out. For each choice set, respondents chose the brand that they would rather try, that would taste better, and that would be less harmful. The authors tested five attributes: pack structure (slim, traditional, lipstick, booklet), brand (du Maurier, Vogue), branding (plain, branded), warning label size (50%, 75%), and price ($8.45, $10.45) (Kotnowski et al., 2016). The authors found that respondents would rather try lower-priced cigarettes than higher-priced ones, and would rather try branded packs than plain packs. Respondents thought that lower-priced cigarettes would taste better than higher-priced cigarettes, and that branded packs would taste better than plain packs.

Babineau & Clancy (2015) used a sample of 1378 Irish 16- to 17-year-old school students (smokers and non-smokers). The authors considered plain packaging, but did not use a conditional logit model. Each respondent was presented with a total of ten choice sets. Nine choice sets had two cigarette packs of the same brand to choose from, while one choice set had six cigarette packs to choose from. The nine-pair pack comparisons were: three top cigarette brands (Silk Cut, Marlboro, Benson & Hedges) x 3 levels of standardisation: (1) the then-current branded pack with pictorial warning, (2) proposed EU packs with larger, dual-sided text and pictorial health warnings on 65% of the pack, with the fonts and colours retained, and (3) plain packs. The only attribute changing in each choice set was the three levels of standardisation.

Participants were asked to select their preferred pack for a series of outcome questions: (1) attractiveness, (2) health risk, and (3) attributes of a typical smoker. The authors used Chi-squared tests to compare the probability that participants would select each of the three types of packs. The authors also used GEE regression models, which provided a framework for analyzing correlated data (Hardin, 2005). GEE models allowed Babineau & Clancy (2015) to account for the correlation between individual participants' scores when choosing different packs, and also for correlations that may have appeared due to the clustered nature of the classroom (the survey was a school-based pen and paper survey).

Packs with more branding elements were thought to be healthier than plain packs for Silk Cut, Marlboro, and Benson & Hedges. Results from GEE binary regressions indicated that gender was a significant predictor of pack attractiveness for Silk Cut, with females being more likely to find the EU packs attractive. The authors also found that the removal of brand identifiers, including colour, font, and embossing, reduced the perceived appeal of cigarette packs for young people across all three tested brands. Plain packs were seen as less attractive, less healthy, and smoked by less popular people than branded packs.

In their descriptive analysis, the authors note that slightly more young people reported using roll-your-own (RYO) cigarettes (11.8%) than manufactured cigarettes (10.9%). RYO prevalence is an important consideration when designing DCEs and formulating policy. It may be easier for RYO smokers to avoid seeing packaging if they repack the tobacco into another pack with no health warnings. Since loose tobacco typically lasts longer than a pack of cigarettes, smokers may be willing to repack loose tobacco, whereas repacking manufactured cigarettes might require more effort. Since RYO use in South Africa is low, RYO was not considered in the experimental design.

Given that only one paper (Kotnowski et al., 2016) evaluated plain packaging and price, the current study is a valuable contribution to the literature.

Warnings on individual sticks

Putting warnings on individual cigarettes has been investigated by several authors (Drovandi et al., 2019a; Drovandi et al., 2019b; Gallopel-Morvan, Droulers & Pantin-Sohier, 2019; Hoek et al., 2016; Lund & Scheffels, 2018; Mitchell et al., 2021; Moodie et al., 2020).

Moodie et al. (2020) collected data from 120 Scottish participants assigned to one of 20 focus groups. The authors explored respondents' perceptions regarding cigarettes that displayed the warning 'Smoking kills' on each individual cigarette. Participants were allocated to groups based on age, sex, and SES. Those in younger groups mentioned stubbing cigarettes out early, reducing consumption, or quitting. The consensus was that warnings on individual cigarettes would be off-putting for young people, non-smokers, and those just starting to smoke.

Drovandi et al. (2019b) interviewed 12 smokers, 13 non-smokers, and 2 ex-smokers. The authors sampled first-year undergraduate university students at an Australian university. Twelve individual cigarette stick warnings were tested. The warning depicting the financial consequences of smoking was considered the most effective.

Drovandi et al. (2019a) investigated the use of eight cigarette stick warnings in Canada, the UK, the US, and Australia, with a total sample size of 687 smokers. Participants were presented with eight cigarette stick warnings in random order. Participants rated the perceived effectiveness of the stick warnings in prompting them to quit on a 5-point Likert scale (from 'not at all effective' to 'very effective'). The cigarette warning describing the financial costs associated with smoking was consistently rated the most effective in all four countries.

Hoek et al. (2016) collected data from 313 New Zealand smokers. Using a Best–Worst experiment the authors found that a 'minutes of life lost' graphic had the strongest dissuasive effect relative to the other sticks tested.

Since testing the effectiveness of cigarette stick warnings using a DCE has not yet been done, this paper will contribute to the literature in this respect.

Becker–DeGroot–Marschak (BDM) Auction

The Becker–DeGroot–Marschak (BDM) auction is used in experimental economics to measure willingness to pay (WTP) (Becker, Degroot & Marschak, 1964). In a BDM auction, each participant submits a bid for a product. A sale price is then randomly drawn from a distribution of prices ranging from zero to a price that is higher than the anticipated maximum bid. If the bid made by the participant is higher than the randomly drawn price, the participant receives the product and pays a price that is equal to the drawn price. If the bid is lower than the randomly drawn price, the participant does not receive or pay anything (Becker, Degroot & Marschak, 1964). This BDM auction is 'demand revealing' in that a participant's best strategy is to place a bid that is equal to the amount they would pay for cigarettes (Monchuk et al., 2007).

Several studies, including Monchuk et al. (2007), Thrasher et al. (2011), Rousu & Thrasher (2013), and Rousu et al. (2014), have used the BDM auction to examine how cigarette labelling affects demand for cigarettes. In all these studies, respondents were recruited in grocery stores in the US. Rousu et al. (2014) is used as an example to illustrate how these auctions work.

Rousu et al. (2014) used the BDM auction to asses WTP for cigarette packs with various levels of health warnings: (1) a text-only label that covered 50% of one side of the package (no warning on the front), (2) a text-only message that covered 50% of the lower half of the front, back and one side of the package, and (3) a text message with pictorial image of mouth cancer, covering 50% of the lower half of the front, back and one side of the package. The sample of 146 smokers was recruited in grocery stores in four US cities. As an incentive, respondents were offered $15 to participate. Respondents practiced the auction with two rounds of candy bars.

Each respondent was shown two of the three designs. All participants saw the less restrictive label first (e.g., a text only message that covered 50% of the lower half of the front, back and one side of the package), then the more restrictive label second (e.g., a text message with pictorial image of mouth cancer, covering 50% of the lower half of the front, back and one side of the package). The information the authors were evaluating was that on the second, more restrictive label. The information on the more restrictive label cannot be 'taken away' once it has been provided (Rousu et al., 2014). The selected price was then randomly chosen. If the participant bid more than this value, they paid the selected price and received the package.

Rousu et al. (2014) found that average willingness-to-pay (WTP) for the cigarette pack with the text warnings on the front label were not statistically different from WTP for the cigarette pack with no front label (but with a text warning on the side). The authors found that 53% of participants (n=47) bid differently when presented with the pictorial label than with the side text label, while 60% of participants (n=48) bid differently when presented with the pictorial label versus the front-text label.

Although conducting auctions face-to-face using real cigarette packs would have been ideal for the current study, this was infeasible because of the COVID-19 pandemic and the associated lockdowns. Hypothetical auctions were therefore conducted online after the DCE.

METHODS AND DATA

The experiment done in South Africa is part of a research grant funded by International Development Research Centre, through the Global Alliance for Chronic Diseases research programme. The research grant included colleagues from Canada, Colombia, Chile, Vietnam, and Ecuador. We received guidance from two DCE experts, Professor Emmanouil Mentzakis (Economics Department, University of Southampton), and Associate Professor Neil Buckley (Department of Economics, York University). Pretesting of the survey instrument occurred in Canada. The survey instrument was then adjusted by each country lead to be context relevant.

In each country, the country’s current pack was tested against plain packs with graphic health warnings. For example, the current pack in South Africa is a branded pack with only written health warnings, while the current pack in Vietnam is a branded pack with graphic health warnings. Pre-testing of the South African instrument was done on a sample of 20 respondents. Minor adjustments were made.

Primary data were collected online using LimeSurvey. On 18 and 29 May 2021, emails were sent to all 28 271 registered University of Cape Town (UCT) students. The existing literature indicates that GHWs on tobacco products are effective across a wide range of tobacco-related outcomes among young people (Francis et al., 2019). Both smokers and non-smokers were sampled. Sampling smokers and non-smokers allowed me to investigate reactions to plain packs, price, and cigarette stick warnings among those who already smoke, and those who might consider smoking. Since illicit cigarette trade in South Africa is high, estimated at 30–35% in 2017 (chapter 4 of this thesis), it was accounted for in the experimental design.

The experiment consisted of two designs: the first included illicit packs (blocks 1 and 2), and the second excluded illicit packs (block 3). To achieve an equal split of three groups, students were asked to complete a survey based on their birth month (block 1: January–April, block 2: May−August, block 3: September−December). Participation was incentivised by offering the chance to win one of five R1000 (USD 68, using the average ZAR/USD exchange rate for 2021) Takealot vouchers. Data from seven students who submitted multiple surveys were deleted.

To obtain sufficient data for a robust analysis, and to reduce respondent fatigue, each student was presented with seven choice sets. One of these seven choice sets included a dominant choice (i.e., no trade-offs) to check if respondents were paying attention. The choice sets in this fractional factorial design, (Appendix: Tables A1−A3), were designed using Ngene software. I choose a design that minimised the D-error (the D-error for design 1 is 0.22 and the D-error for design 3 is 0.34).

I included only two packaging options in the experiment: current branded pack (with a written health warning) and plain pack (with GHW) for two reasons: (1) South Africa's proposal is to move from current packing to plain packaging (with GHW), and not just a branded pack with GHW (Republic of South Africa: Department of Health, 9 May 2018), and (2) extensive evidence from experimental psychology suggests that there is a limit to how much information respondents can meaningfully handle while making a decision (Payne, Bettman & Johnson, 1993). Complicated experimental designs challenge cognitive ability, lowering respondent efficiency and offsetting gains from statistical efficiency (Payne, Bettman & Johnson, 1993). Keeping the design simple meant that the respondents were not overburdened.

Each choice set had four alternatives from which the respondent could choose: three cigarette packs, and an opt-out option (no pack chosen). The brand Peter Stuyvesant was chosen as it is a popular mid-priced cigarette brand in South Africa that most people recognise. The brand Caesar was chosen to represent a low-cost illicit brand. Illicit packs were included so that the experiment represented reality as closely as possible. In the event that respondents always chose the illicit pack, a second design was created. The first design (blocks 1 and 2) included two Peter Stuyvesant packs and a Caesar pack, while the second design (block 3) included three Peter Stuyvesant packs.

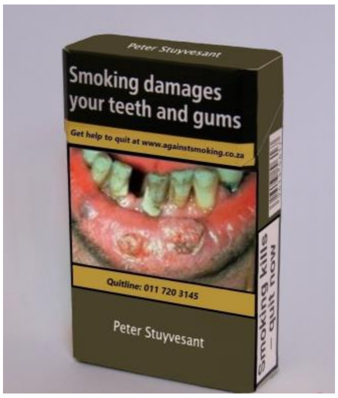
Legal pack:

The attributes of the legal packs were:

1. **Price**: Price levels were chosen that centred around the market price (R42) of Peter Stuyvesant cigarettes when the survey was conducted in May 2021. The price levels for blocks 1 and 2 were R36, R40, R44, and R48. In block 3, two additional levels were added (R32 and R52).
2. **Packaging**: The branded pack is the current pack with a written health warning on 20% of the front of the pack, and a plain pack (with 75% GHW) was created in accordance with the Australian plain packaging requirements: the pack surface colour is Pantone 448C (drab dark brown) and the brand name was displayed in a plain font (Australian Government: Department of Health, 2014a) (Figure 3.1). The GHW image of damaged teeth and gums was consistent in the experiment, as changing the image may have confounded the results.

Figure 3.1: Cigarette packs

Branded pack with written health warning (current pack)



Plain pack with 75% GHW

3. **Warnings on individual cigarettes**: The branded stick with no health warning was the current Peter Stuyvesant stick, and the non-branded stick included the warning 'Smoking causes cancer' (Figure 3.2).

Figure 3.2: Cigarettes sticks

Branded stick with no health warning

Stick with health warning and no branding

Illicit pack

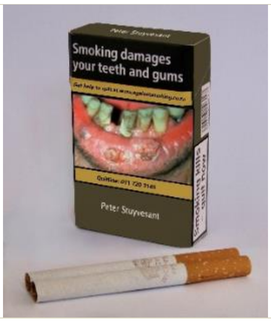
The brand Caesar was used to represent illicit cigarette packs (option C in Figure 3.3). The features of the illicit pack did not change in each choice set. Unlike warnings on sticks, which was an *attribute*, the illicit pack was an *alternative*. The only attribute that changed was the price (R17 and R20). Since consumers would not necessarily have known that Caesar is an illicit brand, this was explained before the experiment began. In South Africa, illegal cigarettes are typically cigarettes sold without excise and VAT paid to the South African Revenue Service. At the time of the survey in 2021, the excise tax on a pack of 20 cigarettes was R18.79. If a pack was sold for R20 or less, the low price indicated that taxes had not been paid, making the pack illegal. A smoker cannot tell just by looking at the pack whether it is legal or not, as illegal manufacturers comply with the government's packaging requirements (e.g., written health warnings)'.

<u>Questions respondents were asked:</u>

In each choice set, respondents were asked two questions. The first question differed for smokers and non-smokers, but the second was the same for both smokers and non-smokers.

Smokers were asked: (1) ‘*If these were the only options you had to choose from, which would you be most likely to buy?*’ with options A, B, C, or ‘None of the above’. Non-smokers were asked (1) ‘*If these were the only options available, which one would most likely encourage someone like you to try smoking?*’ with options A, B, C, or ‘Other answer’. For the second question, both smokers and non-smokers were asked ‘*Which of these do you think would pose the least risk to your health?*’ with options A, B, C, or ‘Other. Please explain’. An example of a choice set (block 1 choice set 1) is presented in Figure 3.3. Option A is a branded pack with no stick warnings, option B is a plain pack with no stick warnings, and option C is the illicit pack.

Figure 3.3: Choice set 1 of design 1 (block 1) for smokers

A	B	C
		
R48	R36	R17

Opt-out options were included so that respondents were not forced to choose a pack, as this might have resulted in them endorsing a package design that they would not otherwise have chosen. Respondents were instructed that choosing *‘none of the above’* implied that the respondent would choose not to smoke.

The fifth choice set in each block included a dominant choice, which showed whether respondents were concentrating and answering consistently. In design 1 (blocks 1 and 2), the dominant choice (excluding Caesar) is option C (Figure 3.4). There are no trade-offs between options A and C: option A is a plain pack with warnings on individual sticks, and it is more expensive (R40) than option C (branded pack with no stick warnings, priced at R36).

Figure 3.4: Choice set with dominant choice in design 1 (blocks 1 and 2)

A	B	C
		
R40	R20	R36

In design 2 (block 3), choice B is the dominant choice as it is cheaper, has the fewest warnings, and is branded (Figure 3.5). I expected that most people would choose option B.

Figure 3.5: Choice set with dominant choice in design 2 (block 3)

A	B	C
		
R52	R44	R48

Hypothetical auction

Smokers also participated in a hypothetical auction to elicit WTP for packs with different attributes. Following Rousu et al. (2014), the Becker–DeGroot–Marschak (BDM) auction was used (Becker, Degroot & Marschak, 1964). Smokers examined two cigarette packs and were asked to place a bid that reflected the maximum they would be willing to pay for them. The WTP reflects the price at which respondents remain indifferent. Two granola bars (premium and discount) were presented to smokers first in order to familiarise respondents with how the auction worked. Clear instructions were given to respondents, together with an example.

The branded packs with no stick warnings were presented to smokers in blocks 1 and 2, the illicit pack in block 1, the plain packs with no stick warnings in blocks 2 and 3, and the plain packs with stick warnings in block 3 (Figure 3.6).

Figure 3.6: Auction packs by block

Smokers were asked: '*What is the maximum amount you are willing to pay for the cigarette pack shown?*' The minimum and maximum amounts that a respondent could enter were R0 and R80. After smokers entered the maximum amount that they were willing to pay for a cigarette pack, LimeSurvey randomly drew a random price between R0 and R80. If the randomly drawn price was higher than the maximum amount smokers were willing to pay, then smokers did not 'purchase' the cigarette pack. If the randomly drawn price was lower or equal to the maximum amount smokers were willing to pay, smokers hypothetically 'purchased' the cigarette pack *at the randomly drawn price* (not at the price the smoker entered as the maximum amount they were willing to pay).

Following the auction for smokers, and the DCE for non-smokers, respondents were asked socio-demographic questions. Smokers were asked additional questions (e.g., cigarette brand preferred, age of smoking onset). To estimate the proportion of smokers who bought illicit cigarettes, the price threshold method was used. The price threshold method identifies a price point (consisting of costs, profits, and taxes) that separates legal cigarettes from illegal cigarettes. The threshold of R25 per pack of 20 cigarettes was based on the following calculation: R18.39 (excise tax in 2021) + R2.76 (VAT on excise) + R3.50 (manufacturing cost) + R0.53 (VAT on manufacturing cost) = R25.18.

Data cleaning

Changes were made to the price variables, and one to the smoking onset variable:

1. For the question '*In the past 30 days, what was the price you paid the last time you purchased a pack of the brand of cigarettes you usually smoke?*', data on cigarette price from two respondents who said they paid R0 for a pack of 20 cigarettes were recoded as missing,
2. Data on cigarette price from one student who stated that he paid R99.99 for a pack of 10 cigarettes were recoded as missing. It is likely that the student was confused because the question said, '*Your answer must be between 0 and 99.99*'.

3. Data on age onset from one student who said he started smoking at age 3 were recoded to missing.

Ethics and software

Ethics clearance was obtained from UCT's Commerce Faculty Ethics in Research Committee (REC 2021/03/004). The data were analysed using Stata version 16.0. The plain pack and the cigarettes with health warnings were designed using Paint 3D.

Setting up the data for the regression analysis

For the regression analysis, the dominant choice sets (choice 5 in each choice set) were excluded. Each respondent contributed 24 lines of data to the dataset (6 choices x 4 alternatives). Table 3.1 shows data for two choice sets from two respondents, one non-smoker, and one smoker. The non-smoker with ID 21, who was assigned to block 1, selected the Caesar pack in choice sets 1 and 2. For the 'least risk' question, person 21 selected the branded pack with no stick warnings in choice set 1, and the branded pack with stick warnings in choice set 2. Smoker with ID 1135, who was assigned to the third block, selected the branded pack with stick warnings in choice sets 1 and 2. For the 'least risk' question, person 1135 selected the branded pack with stick warnings in the first choice set, and the branded pack with no stick warnings in the second choice set.

Dummy variables were created for each pack alternative: (1) plain pack with stick warnings, (2) plain pack with no stick warnings, (3) branded pack with stick warnings, (4) branded pack with no stick warnings, (5) Caesar, and (6) no pack chosen.

Table 3.1: Data from two individuals

ID	Block	Smoker	Choice set	Alternative	Pack	Price	Choice_ buy	Choice_ try	Least Risk
21	1	0	1	1	Branded with no stick warnings	48	.	0	1
21	1	0	1	2	Plain with no stick warnings	36	.	0	0
21	1	0	1	3	Caesar	17	.	1	0
21	1	0	1	4	No pack	0	.	0	0
21	1	0	2	1	Plain with no stick warnings	48	.	0	0
21	1	0	2	2	Caesar	20	.	1	0
21	1	0	2	3	Branded with stick warnings	48	.	0	1
21	1	0	2	4	No pack	0	.	0	0
1135	3	1	1	1	Plain with no stick warnings	52	0	.	0
1135	3	1	1	2	Branded with stick warnings	52	1	.	1
1135	3	1	1	3	Plain with stick warnings	48	0	.	0
1135	3	1	1	4	No pack	0	0	.	0
1135	3	1	2	1	Branded with stick warnings	32	1	.	0
1135	3	1	2	2	Plain with no stick warnings	32	0	.	0
1135	3	1	2	3	Branded with no stick warnings	52	0	.	1
1135	3	1	2	4	No pack	0	0	.	0

Regression analysis

Conditional logit models are used when the choice among alternatives is modelled as a function of the characteristics of the *alternatives*, rather than (or in addition to) the characteristics of the *individual* making the choice (Hoffman & Duncan, 1988). This is a fixed-effects model, where the probability of selecting an alternative is only affected by the attributes that change within a choice set. All other variables for each individual (e.g., sex, race, SES) were constant in the four alternatives and were therefore not included in the model as separate variables. However, to allow for heterogeneity based on observable characteristics (e.g., sex, race, and SES), regressions that included interactions terms were investigated. In these regressions, all attributes were interacted with either sex, race, or SES.

Separate conditional logit regressions were computed for three outcomes: intention to buy (smokers), intention to try (non-smokers), and perceptions of product harm (smokers and non-smokers). The dependent variable was the pack chosen for each of these three outcomes, and the independent variables were the dummy variables for packs and the pack prices. Utility was derived from the underlying attributes of the pack, and individuals' preferences (as summarised by their utility function) were revealed through their choices. The indirect utility (*V*) was assumed to be linear and additive:

$V = \beta_1$ Plain pack with stick warnings + β_2 Plain pack with no stick warnings + β_3 Branded pack with stick warnings + β_4 Price of Peter Stuyvesant pack + β_5 Caesar pack + β_6 Price of Caesar pack + β_7 No pack

The base pack was the branded Peter Stuyvesant pack with no stick warnings (i.e., the current pack). The Stata command for the estimation of the choice model for blocks 1 and 2 was:

```
clogit choice_buy pack2-pack4 price_PS Caesar price_Caesar none if smoker==1, group(grp) cluster(id)
```

where `clogit` specified the conditional logit model (this estimates McFadden's choice model), '`choice_buy`' was the dependent variable (which pack the respondent chose), followed by the regressors, `group(grp)` indicated which observations to group together to represent one choice, and `cluster(id)` indicated clustering at the respondent level. The command for the other regressions was similar, except that `choice_try` and `risk` replaced `choice_buy`. For the `choice_try` regressions, `smoker==1` was replaced with `smoker==0`. For the risk regressions `smoker==1` was deleted so that both smokers and non-smokers were included in the regressions. For block 3, `Caesar` and `price_Caesar` were omitted from the command.

To estimate the predicted probabilities, the following formula was used:

$$\Pr(choice = i) = \frac{e^{V(\beta, X_i)}}{\sum_j e^{V(\beta, X_j)}}$$

Where $V(\beta, X_i)$ is the observed portion of the function for pack *i*, and *i* is one pack among a set of *j* packs. The probability of choosing pack *i* is a function of pack *i* and of all the other packs presented (Hauber et al., 2016).

RESULTS

Descriptive statistics: smokers and non-smokers

Complete, valid responses were collected from 1382 UCT students. Students who attempted to complete the survey on a mobile device (558) or a tablet (54) were asked to return to the survey once they were on a laptop or desktop. Some of these students returned to the survey but others did not.

Although IP address data were captured, it was not possible to use this data to see how many students returned to the survey, as many students, specifically those on campus, in residence, or living in shared accommodation, shared an IP address. For example, one IP address was used by 22 respondents who completed the survey. These were 22 unique students, since students were required to provide their student numbers at the end of the survey to enter the prize draw, and students who completed the survey more than once were deleted. A total of 102 students shared an IP address with at least one other student who also submitted the survey.

Of the 1382 students who completed the survey, block 1 (design 1) was completed by 448 students, block 2 (design 1) by 463, and block 3 (design 2), by 471 (Table 3.2). This represented a response rate of 4.9% (1382/28 271) of all UCT students. All choice sets and responses are provided in the Appendix (Tables A1−A3). Over a quarter of students who completed the survey were current smokers (n=368) at the time of the survey. Respondents were predominantly African (40.5%), followed by White (31.1%), Coloured (17.2%), and Asian/Indian (6.8%).

To compare the survey data to the actual UCT student population, I obtained data on UCT students from the Chief Information Officer at UCT's Institutional Information Unit. UCT does not ask applicants to declare their population group as part of the application process. Although students were asked to declare their population group upon registration, many choose not to. In 2021, one-third of students opted not to declare their population group when they registered for their degrees. Given the incomplete data for the UCT population, it was not possible to compare the population groups in the survey accurately to those of the actual population. However, other comparisons were possible.

There were more female than male respondents in the survey (61% compared to 37%). Similarly, there were more female students at UCT than males, but to a lesser degree (54% compared to 46%).

In relation to the actual population of students, relatively more first-year undergraduate students completed the survey (31.3% compared to the actual proportion of 20.9% first-year students overall). The proportion of Honours students in the survey and in the actual population was identical (11.1%). Relatively fewer Masters' students completed the survey relative to their share of the actual population (11.9% compared to 17.9%). Given the higher proportion of first-year undergraduate students, the age distribution of respondents was not surprising: there was a higher proportion of 18- and 19-year-olds (17.7.% and 17.4%) in the survey population than in the actual population (2.9% and 11.3%). This was likely due to younger students still being willing to complete surveys, whereas older students are tired of doing so. Indeed, students who were 25 years and older comprised only 14.4% of the survey population, compared to 28.7% of the actual student population in this age group.

Very few students from the Engineering and Built Environment faculty completed the survey (n=3; 0.2%). This may be due to a lack of interest in the topic. A higher proportion of students from the Commerce faculty responded to the survey than those in the actual population (29.5% compared to 24.2%). The proportions in the other faculties were broadly similar. 90.3% of respondents were South African, which was somewhat higher than the actual student population (85%).

Data on parental education was only available for the actual population of first-year students. Although I have this data for all surveyed students, I only included it for first-years so that the two samples were comparable. Over half of the respondents in first year (53.7%) had a mother with tertiary education. Just under a half of respondents in first year (46.8%) had a father with tertiary education.

Given the lack of data on population group, and discrepancies in other variables, it was not possible to conclude that the sample of 1382 students was representative of the actual UCT student population. While a weighting exercise could have adjusted for these discrepancies, this was not possible as 32.2% of the total UCT student population did not declare their population group (a critical variable in a weighting exercise). As such, the analysis that follows does not claim to be representative of the UCT student population.

Table 3.2: Descriptive statistics: smokers and non-smokers

	Description	Sample	Total UCT student population in 2021
Total		1382	28 271 (100%)
Block	1	448 (32.4%)	--
	2	463 (33.5%)	--
	3	471 (34.1%)	--
Smoker	All blocks	368 (26.6%)	--
	Block 1	124 (27.7%)	--
	Block 2	122 (26.4%)	--
	Block 3	122 (25.9%)	--
Population group	African	560 (40.5%)	9357 (33.1%)
	Coloured	237 (17.2%)	3370 (11.9%)
	Asian/Indian	94 (6.8%)	1563 (5.5%)
	White	431 (31.1%)	4713 (16.7%)
	Other	16 (1.2%)	170 (0.6%)
	Undeclared	44 (3.2%)	9098 (32.2%)
Sex	Males	510 (37.0%)	12 962 (45.8%)
	Females	844 (61.0%)	15 281 (54.1%)
	Other/Prefer not to respond	28 (2.0%)	28 (0.1%)
Year of study	Undergrad year 1	432 (31.3%)	5915 (20.9%)
	Undergrad year 2	222 (16.1%)	5490 (19.4%)
	Undergrad year 3	195 (14.4%)	4487 (15.9%)
	Undergrad year 4−6	131 (9.5%)	1964 (6.9%)
	Honours/PG Diploma	154 (11.1%)	3131 (11.1%)
	Masters	165 (11.9%)	5054 (17.9%)
	PhD	58 (4.2%)	1793 (6.3%)
	Occasional (non-degree) students	--	437 (1.6%)
	Prefer not to respond/Don’t know	25 (1.8%)	--
Faculty	Commerce	413 (39.9%)	7465 (26.4%)
	Engineering & Built Environment	3 (0.2%)	4468 (15.8%)
	Health Sciences	221 (16.0%)	4467 (15.8%)
	Humanities	442 (32.2%)	7442 (26.3%)
	Law	64 (4.6%)	1293 (4.6%)
	Science	236 (17.1%)	3136 (11.1%)
SA citizen	Yes	1253 (90.3%)	24043 (85.0%)
	No	126 (9.1%)	4158 (14.7%)
	Prefer not to respond/Unknown	8 (0.6%)	70 (0.2%)
Age	≥18	244 (17.7%)	834 (3.1%)
	19	241 (17.4%)	3204 (11.3%)
	20	184 (13.3%)	3729 (13.2%)
	21	197 (14.3%)	3746 (13.3%)
	22	119 (8.6%)	3257 (11.5%)
	23	104 (7.5%)	2463 (8.7%)
	24	55 (4.0%)	1791 (6.3%)
	25	39 (2.8%)	1118 (4%)
	>25	199 (14.4%)	8126 (28.7%)
	Unknown	--	3 (0.0%)
Mother’s education (first year students only)	Unknown	26 (6.0%)	307(6.3%)
	Less than grade 12	56 (13.0%)	797 (16.5%)
	Grade 12	119 (27.3%)	1219 (25.2%)
	Complete tertiary	232 (53.7%)	2514(52.0%)

Father's education (first year students only)	Unknown	56 (13.0%)	761 (15.7%)
	Less than grade 12	52 (12.0%)	727 (15.0%)
	Grade 12	122 (28.2%)	1031 (21.3%)
	Complete tertiary	202 (46.8%)	2318 (47.9%)
Median age		21 years	22 years
Average time to complete survey	Smokers (n=368)	18 minutes	--
	Non-smokers (n=1014)	15 minutes	--
Used an e-cigarette (e.g., JUUL, Vype, Twisp), or any heated tobacco products (e.g., IQOS) in past 30 days	Yes	228 (16.5%)	
	No	1144 (82.8%)	
	Prefer not to respond / Don't know	10 (0.7%)	
Dual users (cigarettes & e-cigarettes/heated tobacco products)		153 (11.1%)	

Note: Data on total UCT student were obtained from Jane Hendry (Chief Information Officer, Institutional Information Unit, UCT)

Descriptive statistics: smokers only

The most popular cigarette brand among smokers was Marlboro, smoked by just over half of the smokers in the sample (Table 3.3). Camel was the next most popular brand, smoked by 10.1% of smokers. Three-quarters of students who smoked had bought cigarettes in the past 30 days, most of whom bought them in packs of 20 cigarettes (68.2%), with an average price of R42.00 per pack. Around 14% of students bought single cigarettes, with an average price of R3.10 per stick. Based on a price threshold of R25 per pack of 20 cigarettes (R1.25 per cigarette), 5.5% of smokers bought illicit cigarettes. This was lower than in the general population, which was expected, given that UCT students as a sample are a very different from the general population. Van der Zee, Van Walbeek & Magadla (2019), who looked at national data from 2017, found that smokers who are older, have lower levels of education, and have lower household per capita income were more likely to purchase illicit cigarettes.

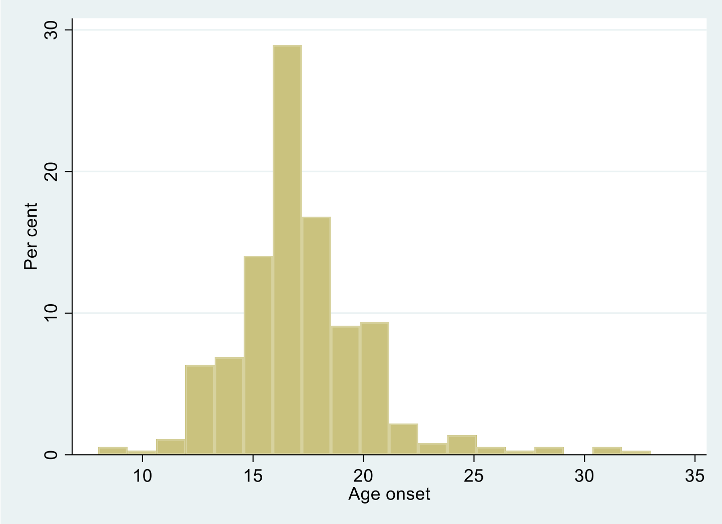
About a third of students smoked their first cigarette 60 minutes or less after waking up. Half of students smoked their first cigarette more than an hour after waking up. 16.9% preferred not to respond or answered 'don't know' to this question.

Table 3.3: Descriptive statistics: smokers only

Variable	Description	n (%)
What brand of cigarettes do you usually smoke?	Marlboro	192 (52.2%)
	Camel	37 (10.1%)
	Peter Stuyvesant	19 (5.2%)
	Chesterfield	12 (3.3%)
	Pall Mall	12 (3.3%)
	I don't have a usual brand	29 (7.9%)
	Other	41 (11.1%)
	Rolling tobacco	22 (6.0%)
	Prefer not to respond / Don't know	4 (1.1%)
Did you purchase cigarettes in the past 30 days?	Yes	280 (76.1%)
	No	84 (22.8%)
	Prefer not to respond / Don't know	4 (1.1%)
Did you purchase a carton, pack, or single cigarettes?	Carton of 200 cigarettes	9 (3.2%)
	Loose/single stick	44 (15.7%)
	Pack of 30 cigarettes	4 (1.4%)
	Pack of 20 cigarettes	191 (68.2%)
	Pack of 10 cigarettes	17 (6.1%)
	Rolling tobacco	13 (4.6%)
	Prefer not to respond / Don't know	2 (0.7%)
Carton price	Median: R400, mean: R379.33, std dev: R128.70, min: R100.00, max: R530.00	
Pack price (30 cigs)	Median: R47.50, mean: R44.75, std dev: R12.04, min: R28.00, max: R56.00	
Pack price (20 cigs)	Median: R44.00, mean: R42.00, std dev R8.64, min: R12.00, max: R70.00	
Pack price (10 cigs)	Median: R22.00, mean: R25.13, std dev R9.24, min: R16.00, max: R50.00	
Single cigarette price	Median: R2.50, mean: R3.10, std dev R1.65, min: R1.50, max: R9.00	
How soon after you wake up do you usually smoke your first cigarette?	Within 5 minutes	19 (5.2%)
	6 to 30 minutes	59 (16.0%)
	31 to 60 minutes	44 (12.0%)
	More than 60 minutes	184 (50%)
	Prefer not to respond / Don't know	62 (16.9%)
How much do you think people risk harming themselves when they smoke cigarettes daily?	Great risk	239 (65.0%)
	Moderate risk	108 (29.4%)
	Slight risk	10 (2.7%)
	No risk	1 (0.3%)
	Prefer not to respond / Don't know	12 (2.7%)
In the past 12 months, did you stop smoking for at least 24 hours because you were trying to reduce or quit?	Yes	274 (74.5%)
	No	85 (23.1%)
	Prefer not to respond / Don't know	9 (2.5%)
Do you intend to quit smoking in the next six months?	Yes	140 (40.4%)
	No	81 (23.3%)
	Maybe	126 (36.3%)
At what age did you smoke your first whole cigarette?	n=363, mean: 17.1, median: 17, std dev: 3.1, min: 6, max: 33	

The average smoking onset age was 17.1 years (standard deviation: 3.1 years) (Figure 3.7). 90% of smokers had started smoking by the age of 20.

Figure 3.7: Smoking onset age (n=363)



Checking if respondents were paying attention

In each block, a choice set with a dominant choice was added to check that participants were paying attention (see results and choice sets in Appendix table A4). In these choice sets, there was an obvious choice, as there were no trade-offs to consider. Responses to the choice sets with a dominant choice indicated that respondents generally answered the questions appropriately. For example, 85.3% of smokers in design 2 (block 3) chose the dominant choice (pack B) (9.3% chose no pack, 4.1% chose pack A, and 0.8% chose pack C).

For the regression analysis, the dominance questions (question 5 in all 3 blocks) were deleted. Design 1 (blocks 1 and 2) were analysed together as both blocks included illicit packs. Only two people chose the same pack in all choice sets (either the first pack, the second pack, or the third pack), which may indicate mindless clicking through the questions. In blocks 1 and 2, the same non-smoker (id 775) answered pack B in all six *likely to try* questions and all six *least risk to health* questions. Similarly, in block 3 the same smoker (id 929) answered pack B in all six *likely to buy* questions, and in all six *least risk to health* questions. The fact that only one student clicked on the same option for all questions indicates that very few students were clicking through the questionnaire without engaging the content. These observations were not deleted, as it is possible that these respondents selected these options deliberately.

Table 3.4: Number of people who chose same alternative in every choice set

	Design 1: blocks 1 & 2 (with illicit pack)			Design 2: block 3 (no illicit pack)		
	Buy (smokers)	Try (non-smokers)	Risk (smokers & non-smokers)	Buy (smokers)	Try (non-smokers)	Risk (smokers & non-smokers)
Pack A	0	0	0	0	0	0
Pack B	0	1	1	1	0	1
Pack C	0	0	0	0	0	0
None	11	46	146	6	17	101
None (% of total)	(4.5%)	(6.9%)	(16.0%)	(4.9%)	(4.9%)	(21.4%)
Total respondents	246	665	911	122	349	471

In blocks 1 and 2, 11 smokers (4.5%), 46 non-smokers (6.9%), and 146 smokers and non-smokers (16.9%) answered ‘none’ to all six questions (Table 3.4). In blocks 1 and 2, these 11 smokers would rather not have bought any cigarette pack (Peter Stuyvesant or Caesar), 46 non-smokers would rather not have tried any cigarettes, 146 smokers and non-smokers did not think one pack was less risky than another. This this may indicate that these respondents perceived the risk of cigarettes to be equal, regardless of the brand, warning labels, or price. Similarly, in block 3, 6 smokers (4.9%), 17 non-smokers (4.9%), and 101 smokers and non-smokers (21.4%) chose none.

Regression results

The coefficients from a conditional logit regression provide the direction of the effects and statistical significance. A positive (negative) coefficient indicates an increase (decrease) in utility/attractiveness compared to the baseline level of the attribute, hereafter ‘base’ (in this case, the base is the branded pack with no stick warnings). The coefficients by themselves do not provide a quantitative interpretation. Rather, the coefficients on the various packs were compared to the base pack in terms of magnitude, direction, and statistical significance, and to other packs. To translate coefficients into something tangible, predicted probabilities were calculated from each conditional logit regression (see section ‘Predicted probabilities’).

Regression results are first reported for design 1 (blocks 1 and 2, which included illicit packs) (Table 3.5), and then design 2 (block 3, which excluded illicit packs) (Table 3.6). The two sets of results include three regressions related to each of the questions: (1) most likely to buy (addressed to smokers), (2) most likely to try (addressed to non-smokers), and (3) least risk to health (addressed to smokers and non-smokers). The branded pack with no stick warnings (base), plain pack with stick warnings (β_1), plain pack with no stick warnings (β_2), and branded pack with stick warnings (β_3) are all Peter Stuyvesant packs.

Design 1 (included illicit packs)

<u>Design 1: Most likely to buy (Table 3.5 column 1)</u>

Smokers preferred to buy the branded pack with no stick warnings over all the other packs. The plain pack with stick warnings (coefficient of -2.13; 95% CI: -2.51, -1.75) decreased utility/preference compared to the base pack. The same is true for plain pack with no stick warnings (coefficient of -2.28; 95% CI: -2.63, -1.93). If two statistics have overlapping confidence intervals, it is not necessarily true that they are not significantly different (Cornell Statistical Consulting Unit, 2020). The *p*-value (estimated after the regression using the `test` command) for comparing the two means is 0.43, which indicates that the null hypothesis, that the means of the two coefficients are the same, should not be rejected at the 5% level (i.e., the means are the same). For confidence intervals that are not closely overlapping (as is the case here), post-estimation tests were run to check whether or not the means are statically different.

The branded pack with stick warnings also reduced utility (coefficient of -0.56; 95% CI: -0.74, -0.37) compared to the branded pack with no stick warnings, but not as much as the plain pack with stick warnings (-2.13) and the plain pack with no stick warnings (-2.28). The only difference between the base pack, and the branded pack with stick warnings, was the stick warnings. The negative and statistically significant coefficient indicates that stick warnings were effective in reducing people's utility for cigarettes when the pack was branded.

The price coefficient of -0.02 (95% CI: -0.04, -0.01) on the Peter Stuyvesant price variable indicates that smokers are rational economic agents. The higher the price, the less smokers like the pack, regardless of the pack type.

The coefficient of -2.28 (95% CI: -3.28, -1.28) on the Caesar pack indicates that, in general, smokers did not like the illicit pack more than the branded Peter Stuyvesant pack with no stick warnings (base). The price of the Caesar pack did not seem to matter to smokers (the coefficient is not statistically significant). The experimental design may have contributed to its effect not being significant, as the variation in the price of Caesar was limited (R17 and R20) compared to that of the Peter Stuyvesant packs (R32 to R52).

The strong negative and statistically significant coefficient (-2.97; 95% CI: -3.74, -2.20) on the constant (no pack chosen) indicates that not choosing any pack to buy had a negative effect on smokers' utility. Smokers would rather have bought the base pack, than not bought any pack.

The coefficient on 'none' is -2.97 (95% CI: -3.74, -2.20), which is lower than the coefficient on the illicit pack (-2.28; 95% CI: -3.28, -1.28).

Table 3.5: Conditional logit regressions, design 1 (blocks 1 and 2)

	Most likely to buy (smokers)	**Most likely to try** (non-smokers)	**Least risk to health** (smokers & non-smokers)
	(1)	(2)	(3)
Base: Branded pack with no stick warnings	*0.00*	*0.00*	*0.00*
Plain pack with stick warnings (β_1)	-2.13***	-2.54***	-1.99***
	(0.19)	(0.16)	(0.10)
Plain pack with no stick warnings (β_2)	-2.28***	-2.32***	-1.80***
	(0.18)	(0.13)	(0.09)
Branded pack with stick warnings (β_3)	-0.56***	-0.62***	-0.75***
	(0.09)	(0.06)	(0.05)
Price of Peter Stuyvesant pack (β_4)	-0.02***	0.01***	0.02***
	(0.01)	(0.00)	(0.00)
Caesar pack (β_5)	-2.28***	-0.13	-1.88***
	(0.51)	(0.30)	(0.27)
Price of Caesar pack (β_6)	0.03	0.04***	0.08***
	(0.02)	(0.01)	(0.01)
No pack (β_7)	-2.97***	-1.13***	-0.58***
	(0.39)	(0.25)	(0.18)
Observations	5 904	15 960	21 864
Respondents	246	665	911

*Notes: se in parentheses, *** p<0.01, ** p<0.05, * p<0.1*

Design 1: Most likely to try (Table 3.5 column 2)

Like smokers, non-smokers preferred the branded pack over the other packs. Non-smokers preferred the branded pack with stick warnings (coefficient of -0.62; 95% CI: -0.74, -0.50) over the plain pack with stick warnings (coefficient of -2.54; 95% CI: -2.85, -2.22) and the plain pack with no stick warnings (coefficient of -2.32; 95% CI: -2.58, -2.06). The branded pack with the stick warnings had a lower utility than the branded pack with no stick warnings, implying that stick warnings effectively reduced the attractiveness of cigarettes. However, there is no evidence that stick warnings reduced utility when presented with plain packs (there is no statistical difference between the coefficients of -2.54 and -2.32, p=0.14).

The coefficient on the Caesar pack (-0.13; 95% CI: -0.72, 0.46) indicates that non-smokers' utility from the illicit pack was the same as the utility from the base pack (branded pack with no stick warnings). The positive and significant coefficients on the price of Peter Stuyvesant packs (0.01; 95% CI: 0.00, 0.02) and the price of Caesar packs (0.04; 95% CI: 0.02, 0.07) indicate that non-smokers believe that ‘someone like them’ is more likely to try cigarettes with higher prices. Higher prices may signal higher quality.

The negative constant of not choosing any pack is -1.13 (95% CI: -1.62, -0.63), which suggests that non-smoking respondents believe that ‘someone like them’ is more likely to want to try smoking rather than not to try it at all (the question wording is ‘If these were the only options available, which one would most likely encourage someone like you to try smoking?’). There may be some priming of non-smokers in the questionnaire. It seems more likely that without the priming, non-smokers would have preferred not to try any cigarette pack. The magnitude for non-smokers not choosing any pack (-1.13, 95% CI: -1.62, -0.63) is lower than that of smokers (-2.97, 95% CI: -3.74, -2.20). This is not surprising given the addictive nature of cigarettes.

Design 1: Least risk to health (Table 3.5 column 3)

Both smokers and non-smokers thought that all other packs were riskier than the base pack (branded pack with no stick warnings). The plain pack with stick warnings (-1.99; 95% CI: -2.19, -1.78), the plain pack with no stick warnings (-1.80, 95% CI: -1.98, -1.63), and the Caesar pack (-1.88, 95% CI: -2.42, -1.34) were perceived to be equally risky, but more risky than the branded pack with no stick warnings (base). The branded pack with stick warnings (-0.75, 95% CI: -0.85, -0.65) was perceived to be more risky than the branded pack with no stick warnings, but less risky than the plain pack with stick warnings, the plain pack with no stick warnings, and the Caesar pack. The coefficients on the price of Peter Stuyvesant (0.02; 95% CI: 0.01, 0.02) and the price of Caesar (0.08; 95% CI: 0.05, 0.10) indicate that people perceive higher-priced cigarettes to be less risky.

Design 1: Predicted probabilities

Predicted probabilities were calculated using the coefficients from the regressions in Table 3.5. Calculating predicted probabilities allowed the following question to be answered: if the six packs were presented to respondents, how would respondents have split their choices between the six packs? Consider a hypothetical case where a pack of Peter Stuyvesant costs R42 and a pack of Caesar costs R21. These prices were chosen as they are close to market values in 2021. To estimate the predicted probabilities, the following formula, presented in the methods section, was used:

$$\Pr(choice = i) = \frac{e^{V(\beta, X_i)}}{\sum_j e^{V(\beta, X_j)}}$$

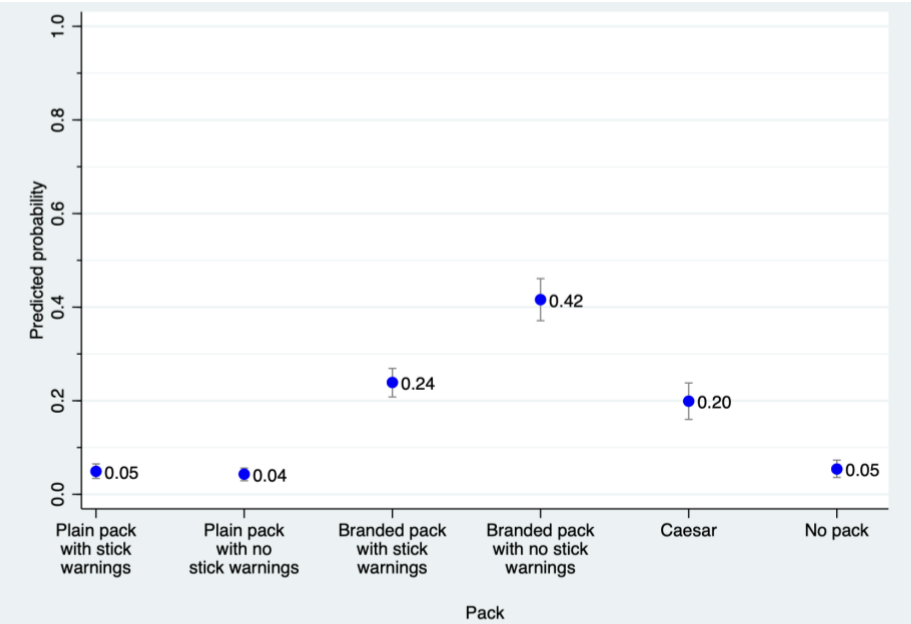
Using the coefficients in Table 3.5 column 1, the predicated probability for the plain pack with stick warnings is:

Pr (plain pack with stick warnings)= $\exp(\beta_1 + \beta_4*42)/(\exp(\beta_1 + \beta_4*42) + \exp(\beta_2 + \beta_4*42) + \exp(\beta_3 + \beta_4*42) + \exp(\beta_4*42) + \exp(\beta_5 + \beta_6*21) + \exp(\beta_7))$
$= \exp(-2.13 + (-0.02)*42)/(\exp(-2.13 + (-0.02)*42) + \exp(-2.28 + (-0.02)*42) + \exp(-0.56 + (-0.02)*42) + \exp((-0.02)*42) + \exp(-2.28 + 0.03*21) + \exp(-2.97))$ = **0.05**

For each of the remaining predicted probabilities, the denominator is the same and the numerator changes: to calculate the predicted probability of β_2 (plain pack with no stick warnings), β_2 replaces β_1 as follows: $\exp(\beta_2 + \beta_4*42)$ instead of $\exp(\beta_1 + \beta_4*42)$. The predicted probabilities for most likely to buy, intention to try, and least risk to health are presented in Figures 3.8−3.10. All these predicted probabilities are based on the assumption that a Peter Stuyvesant pack costs R42 and a Caesar pack costs R21. The predicted probabilities for each regression sum to one.

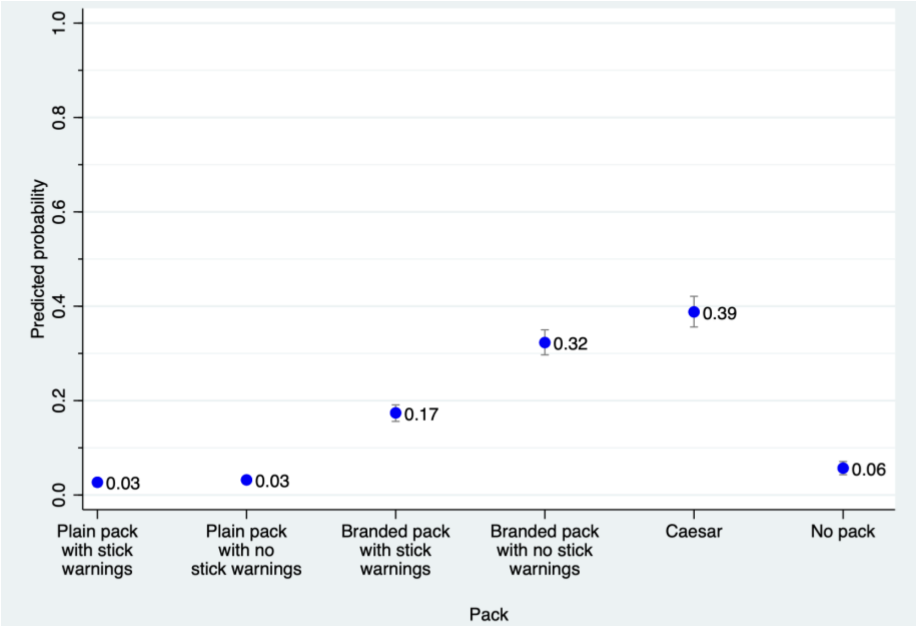
If all six packs were presented to smokers, the probability that they would choose a branded pack with no stick warnings is 0.42, a plain pack with stick warnings 0.05, a plain pack with no stick warnings 0.04, a branded pack with stick warnings 0.24, Caesar pack 0.2, and no pack: 0.05 (Figure 3.8).

Figure 3.8: Predicted probabilities: most likely to buy (smokers)



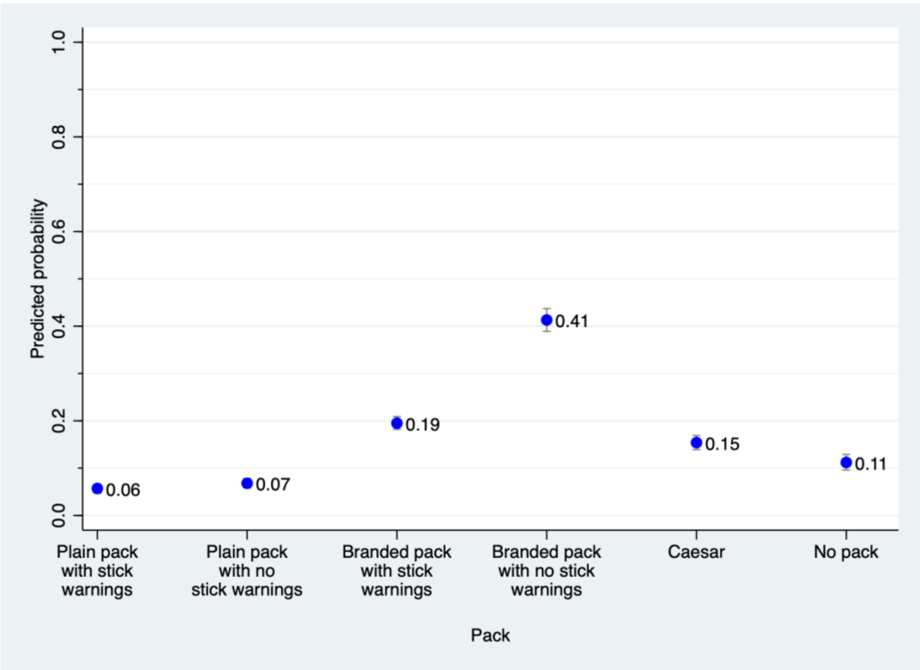
The highest predicted probabilities for the *most likely to try* regressions is 0.39 for the Caesar pack, followed by the branded pack with no stick warnings (0.32) (Figure 3.9). The predicted probabilities for choosing the plain pack with stick warnings (0.03), choosing the plain pack with no stick warnings (0.03), and choosing no pack (0.06) are similar.

Figure 3.9: Predicted probabilities: most likely to try (non-smokers)



The probabilities for the perceptions of risk question (addressed to both smokers and non-smokers) (Figure 3.10) are very similar to the probabilities of the most likely to buy (smokers). The likelihood to buy (or try) cigarettes is strongly correlated with the perceptions of least health risk. Smokers and non-smokers are most likely to choose the branded pack with no stick warnings (0.41).

Figure 3.10: Predicted probabilities: least risk to health (smokers and non-smokers)



Design 2 (no illicit packs)

Design 2: Most likely to buy (Table 3.6 column 1)

Similarly to the results for design 1, smokers preferred to buy the branded pack with no stick warnings over all the other packs. The branded pack with stick warnings was less preferred than the branded pack with no stick warnings, but more preferred than the plain pack with stick warnings and the plain pack with no stick warnings. The coefficient on the plain pack with stick warnings is -1.79 (95% CI: -2.33, -1.26) and the coefficient of the plain pack with no stick warnings is -2.34 (95% CI: -2.78, -1.89). Stick warnings were effective when presented with branded packs: the utility from the branded pack with stick warnings is lower (-0.33; 95% CI: -0.58, -0.07) than the base pack (branded pack with no stick warnings). The negative and significant price coefficient (-0.04; 95% CI: -0.05, -0.02) indicates that smokers preferred lower prices than higher prices. Not choosing any pack reduced utility (-3.53; 95% CI: -4.43, -2.63) compared to choosing the base pack.

Table 3.6: Results from conditional logit, design 2 (block 3)

	Most likely to buy (smokers)	**Most likely to try** (non-smokers)	**Least risk to health** (smokers & non-smokers)
	(1)	(2)	(3)
Base: Branded pack with no stick warnings	*0.00*	*0.00*	*0.00*
Plain pack with stick warnings	-1.79***	-3.25***	-2.34***
	(0.27)	(0.21)	(0.15)
Plain pack with no stick warnings	-2.34***	-3.30***	-1.87***
	(0.23)	(0.19)	(0.12)
Branded pack with stick warnings	-0.33**	-0.74***	-0.91***
	(0.13)	(0.09)	(0.06)
Price of Peter Stuyvesant pack	-0.04***	-0.00	0.03***
	(0.01)	(0.00)	(0.00)
No pack	-3.53***	-2.49***	0.48***
	(0.46)	(0.36)	(0.17)
Observations	2 928	8 376	11 304
Respondents	122	349	471

*Notes: se in parentheses, *** p<0.01, ** p<0.05, * p<0.1*

Design 2: Most likely to try (Table 3.6 column 2)

Non-smokers preferred to try the branded pack with no stick warnings compared to all the other packs. Non-smokers thought that 'someone like them' would have preferred to try the branded pack with no stick warnings rather than any of the other packs. The packs least likely to be tried were the plain pack with stick warnings (-3.25; 95% CI: -3.66, -2.84) and the plain packs with no stick warnings (-3.30; 95% CI: -3.67, -2.93). As before, stick warnings reduced utility when presented with branded packs. The price coefficient is not significant for non-smokers. Choosing no pack versus the base pack reduced utility for non-smokers (-2.49; 95% CI (-3.19 –

-1.78). As in design 1, the magnitude of not choosing any pack is higher among smokers than among non-smokers (-3.53 compared to -2.49).

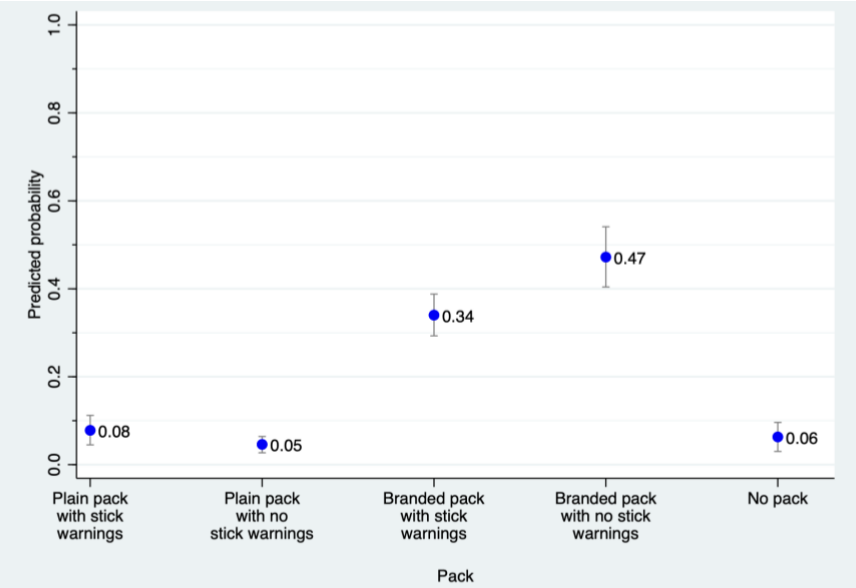
Design 2: Least risk to health (Table 3.6 column 3)

Smokers and non-smokers thought that all packs were riskier than the base pack (branded pack with no stick warnings). The plain pack with stick warnings (-2.34; 95% CI: -2.64, -2.04) was perceived as more risky than the plain pack with no stick warnings (-1.87, 95% CI: -2.09, -1.64). Although the confidence intervals slightly overlap, the *p*-value of 0.00 indicates that these means are statistically different. The branded pack with stick warnings (-0.91, 95% CI: -1.03, -0.79) was perceived to be more risky than the branded pack with no stick warnings, but less risky than the plain pack with stick warnings and the plain pack with no stick warnings. The coefficients on the price of Peter Stuyvesant (0.03; 95% CI: 0.02, 0.04) indicate that people perceive higher-priced cigarettes as less risky.

Design 2: Predicted probabilities

In line with Table 3.6, the predicted probabilities in Figures 3.11−3.13 are also based on the assumption that a Peter Stuyvesant pack costs R42, and a Caesar pack costs R21. The probability of buying a branded pack with no stick warnings is 0.47, and the probability of buying a branded pack with stick warnings is 0.34 (Figure 3.11). The probability of buying the plain pack with stick warnings and the plain pack with no stick warnings is low in comparison (0.08 and 0.05), as is the probability of not buying any pack (0.06).

Figure 3.11: Predicted probabilities: most likely to buy (smokers)

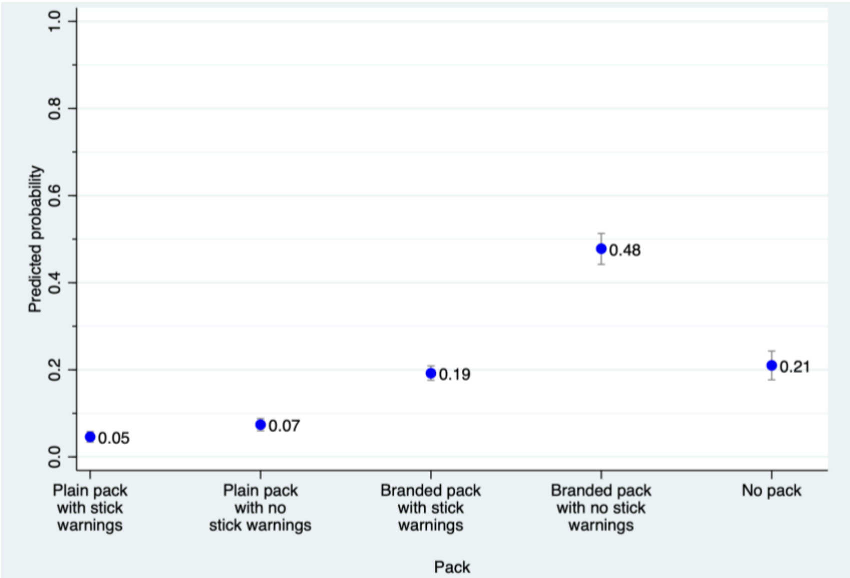


Non-smokers are most likely to try the branded pack with no stick warnings (0.61), followed by the branded pack with stick warnings (0.29) (Figure 3.12). The probability of trying the plain pack with stick warnings (0.02) and the probability of trying the plain pack with no stick warnings (0.02) is lower than those for buying packs (Figure 3.11) with the same features (0.08 and 0.05). This indicates that smokers are more willing to buy packs with health warnings compared to non-smokers.

Figure 3.12: Predicted probabilities: most likely to try (non-smokers)

The probabilities for the 'least risk to health' question are more varied than for the most likely to buy and most likely to try (Figure 3.13). Specifically, the probability of not choosing any pack is 0.21 (compared to 0.06 for buying and 0.06 for trying). Smokers and non-smokers perceive the branded pack with no stick warnings as the pack posing the least harm (0.48).

Figure 3.13: Predicted probabilities: least risk to health (smokers and non-smokers)



Given that sex, race, and SES did not vary within a choice, these variables could not be added into the model directly. However, interaction terms were included whereby each attribute was interacted with sex/race/SES. In almost all cases, the Bayesian Information Criteria (BIC) for the regressions without interaction terms were lower than in the models with interactions terms, indicating that the regressions without interactions are preferred. The small sample size becomes an issue with the interactions; for example, in design 2 there were only 31 African smokers, 25 Coloured smokers, and 58 White/Asian smokers.

Alternative specific constant

The alternative specific constant captures the effect of the position of the packs (whether the pack comes first, second or third). To investigate whether the position of the packs makes a difference to the results, I included three dummy variables (for alternative 1, the dummy receives a value of 1 for alternative 1, and 0 for alternatives 2 and 3). Alternative 1 is the base scenario. Columns 1, 3, and 5 in Table 3.7 are repeated from Table 3.5 for ease of reference (same for columns 1, 3, and 5 in Table 3.8: repeated from Table 3.6). Columns 2,4, and 6 of Tables 3.7 and 3.8 include the alternative specific constants.

The results indicate that adding in alternative specific constants do not change the results in any meaningful way in terms of magnitude and ranking compared to the results that do not include alternative specific constants. Table 3.7 column 2 shows that the third pack was less likely than the first pack to be chosen (significant at the 5% level). There was no difference between the probability of the first pack being chosen compared to the second pack. Even though the third pack was less likely to be chosen than the first pack, this did not change the results much. For example, the coefficient on β_1 changed from –2.13 to –2.12. Given that the results do not change much, and that the BICs for the regressions without the alternative specific constants were lower in all regressions compared to without the alternative specific constants, the preferred regressions remain the regressions without the alternative specific constants (Tables 3.5 and 3.6).

Table 3.7: Adding alternative specific constants to regressions (Design 1: blocks 1 and 2)

	Most likely to buy (smokers)		**Most likely to try** (non-smokers)		**Least risk to health** (smokers & non-smokers)	
	(1)	(2)	(3)	(4)	(5)	(6)
Base: alternative specific constant 1	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
Alternative specific constant 2		-0.05		-0.23***		-0.26***
		(0.08)		(0.06)		(0.05)
Alternative specific constant 3		-0.10**		-0.09***		-0.02
		(0.05)		(0.03)		(0.03)
Base: Branded pack with no stick warnings	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
Plain pack with stick warnings (β_1)	-2.13***	-2.12***	-2.54***	-2.50***	-1.99***	-1.94***
	(0.19)	(0.19)	(0.16)	(0.16)	(0.10)	(0.10)
Plain pack with no stick warnings (β_2)	-2.28***	-2.26***	-2.32***	-2.29***	-1.80***	-1.78***
	(0.18)	(0.18)	(0.13)	(0.13)	(0.09)	(0.09)
Branded pack with stick warnings (β_3)	-0.56***	-0.52***	-0.62***	-0.65***	-0.75***	-0.82***
	(0.09)	(0.10)	(0.06)	(0.07)	(0.05)	(0.05)
Price of Peter Stuyvesant pack (β_4)	-0.02***	-0.02**	0.01***	0.01*	0.02***	0.00
	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)
Caesar pack (β_5)	-2.28***	-1.97***	-0.13	0.00	-1.88***	-2.00***
	(0.51)	(0.52)	(0.30)	(0.31)	(0.27)	(0.29)
Price of Caesar pack (β_6)	0.03	0.02	0.04***	0.02*	0.08***	0.05***
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
No pack (β_7)	-2.97***	-2.79***	-1.13***	-1.45***	-0.58***	-1.22***
	(0.39)	(0.43)	(0.25)	(0.26)	(0.18)	(0.20)
Observations	5 904	5 904	15 960	15 960	21 864	21 864
Respondents	246	246	665	665	911	911

Robust se in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.8: Adding alternative specific constants to regressions (Design 2: block 3)

	Most likely to buy (smokers)		**Most likely to try** (non-smokers)		**Least risk to health** (smokers & non-smokers)	
	(1)	(2)	(3)	(4)	(5)	(6)
Base: alternative specific constant 1	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
Alternative specific constant 2		0.08		0.10*		-0.00
		(0.09)		(0.06)		(0.04)
Alternative specific constant 3		-0.38***		-0.28***		-0.26***
		(0.11)		(0.09)		(0.07)
Base: Branded pack with no stick warnings	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
Plain pack with stick warnings	-1.79***	-1.55***	-3.25***	-3.05***	-2.34***	-2.21***
	(0.27)	(0.26)	(0.21)	(0.21)	(0.15)	(0.14)
Plain pack with no stick warnings	-2.34***	-2.46***	-3.30***	-3.40***	-1.87***	-1.94***
	(0.23)	(0.23)	(0.19)	(0.19)	(0.12)	(0.13)
Branded pack with stick warnings	-0.33**	-0.50***	-0.74***	-0.87***	-0.91***	-1.03***
	(0.13)	(0.15)	(0.09)	(0.10)	(0.06)	(0.07)
Price of Peter Stuyvesant pack	-0.04***	-0.03***	-0.00	0.00	0.03***	0.04***
	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)
No pack	-3.53***	-3.39***	-2.49***	-2.28***	0.48***	0.63***
	(0.46)	(0.46)	(0.36)	(0.37)	(0.17)	(0.19)
Observations	2 928	2 928	8 376	8 376	11 304	11 304
Respondents	122	122	349	349	471	471

Robust se in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Willingness to pay (WTP): Auction results

Smokers' willingness to pay for different cigarette packs is estimated using data from the auction. The sample sizes for plain pack with no stick warnings (n=244) and the branded pack with no stick warnings (n=246) are larger than the plain pack with stick warnings (n=122) and the illicit pack (n=124) because the first two appeared in two of the blocks. Smokers were asked: '*What is the maximum amount you are willing to pay for the cigarette pack shown?*'.

The lowest mean willingness to pay is for the illicit pack at R22.23 (standard deviation: R9.35) (Table 3.9 and Figure 3.14). The highest mean willingness to pay is for the branded pack with no stick warnings (R41.42, 95% CI: R40.10, R42.74). The mean WTP for the plain pack with stick warnings (R28.10, 95% CI: R25.30, R30.80) is not statistically different to the WTP for the plain pack with no stick warnings (R27.60, 95% CI: R25.65, R29.56). The t-test statistic of 0.27 indicates that the null hypothesis, that the two means are the same, should not be rejected at the 5% level.

The WTP for the branded pack versus the plain pack with stick warnings are statistically different (t=11.55). Similarly, the WTP for the branded pack verses the plain pack with no stick warnings are statistically different (t=8.60). For both these t-tests, the null hypothesis that the two mean are the same, should be rejected at the 5% level.

Table 3.9: Auction results (smokers)

	Mean (Rands)	**Median** (Rands)	**95% CI** (Rands)	**Std dev**	**N**
Plain pack, stick warnings	28.07	30.00	(25.30, 30.85)	15.47	122
Plain pack, no stick warnings	27.60	30.00	(25.65, 29.56)	15.49	244
Branded pack, no stick warnings	41.42	40.00	(40.10, 42.74)	10.51	246
Illicit pack	22.23	20.00	(20.56, 23.89)	9.35	124

Figure 3.14: Willingness to pay

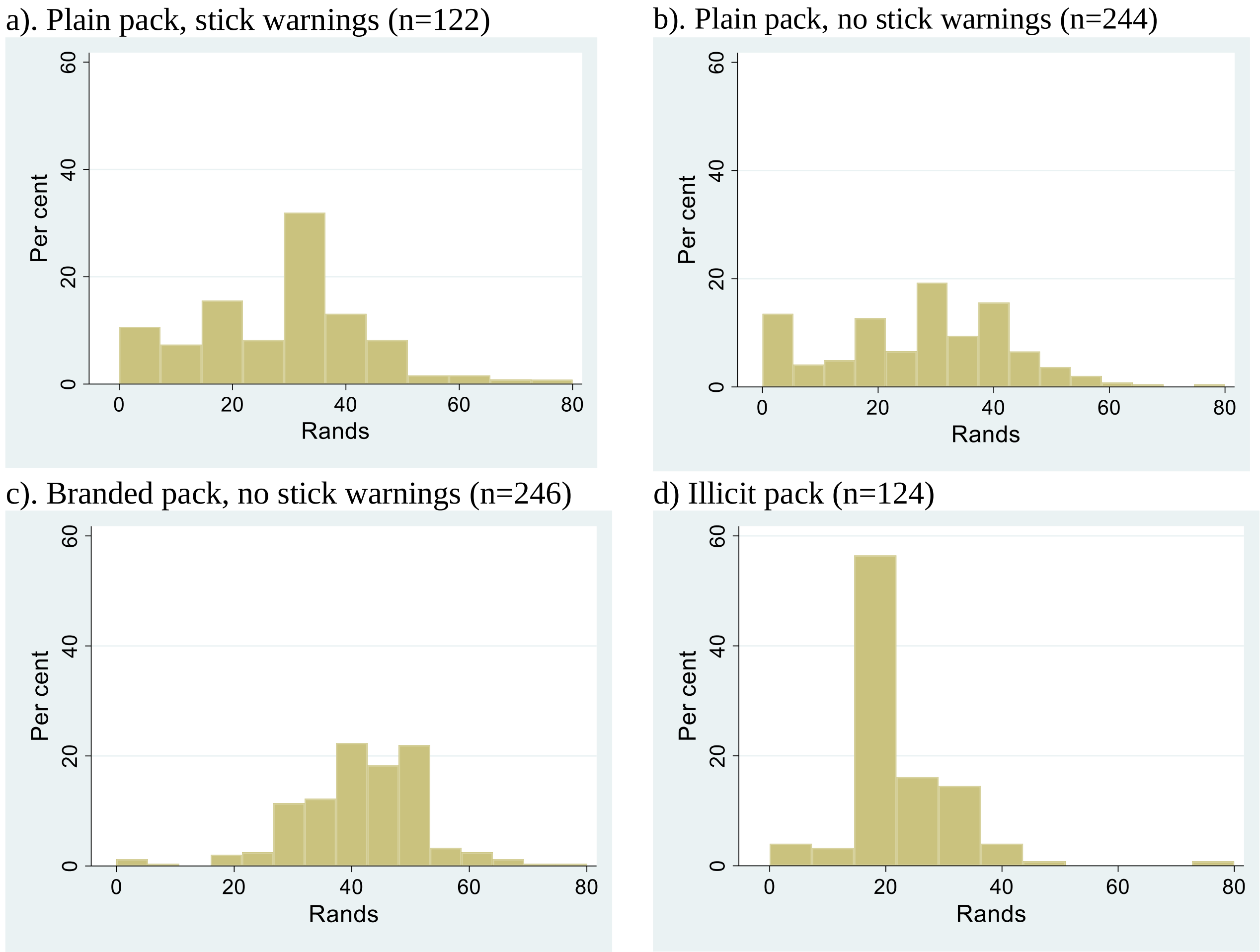
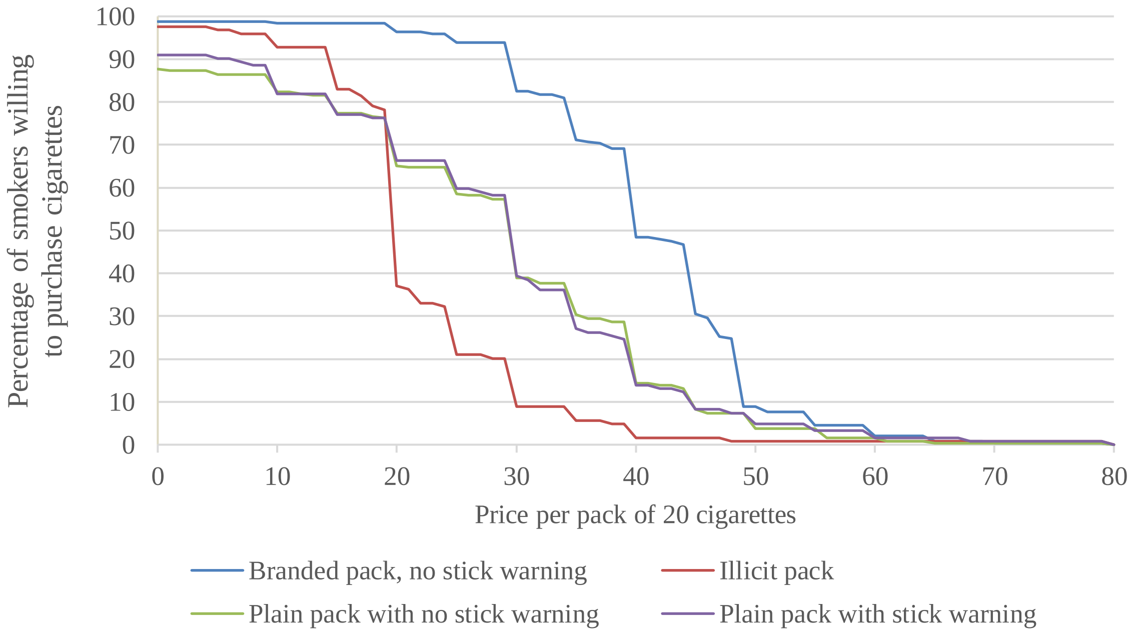


Figure 3.15 shows the percentage of smokers willing to purchase cigarettes at various prices points for the four packs. The results for the plain packs (with and without stick warnings) are near identical. If one had to set a market price of R40 or more across all four types of packs the percentage of smokers willing to purchase cigarettes is as follows: plain packs: 14%, branded pack with no stick warning: 48%, and illicit pack: 2%. The percentage of people who are willing to pay R30 or more is 39% for the plain packs, 83% for the branded pack with no stick warnings, and 9% for the illicit pack. The percentage of people who are willing to pay R20 or more is 65% for the plain packs, 96% for the branded pack with no stick warnings, and 37% for the illicit pack.

Figure 3.15: Percentage of smokers willing to purchase cigarettes by pack type



If packaging policy were changed in favour of enforcing plain packs over branded packs, this analysis suggests that the short-term impact, as long as price stays in the R30 to R40 range, would be a decrease in demand by half or more (83% to 39% for R30 and 48% to 14% for R40). This impact would likely only be in the short-term. Once smokers grow accustomed to the new packaging their demand may increase again in the medium- to long-term.

Some comments made by students

Of the 1382 students who completed the survey, 167 students (12%) provided additional comments at the end of the survey. These comments corroborate the findings from the quantitative research. The comments are grouped into six categories: price, risk, appeal, graphic health warnings, warnings on individual sticks, and Covid-19. Quotations are followed by details of sex (male, female, other, prefer not to respond), age, and smoking status.

Price

For some students, price was the most important factor: *'R20 for a pack of cigarettes is too good to turn down'* (Male, 19, smoker). For others, price was not important: *'The price would not matter to me. Everyone knows smoking is bad, but I would probably be wilfully ignorant when trying smoking. As long as there are few warnings I would probably try'* (Male, 19, non-smoker).

Two students mentioned the trade-off between price and the health warnings: '*My answers were based on low prices but also avoiding the graphic images of smoking damages displayed on cigarette packaging'* (Male, 22, non-smoker), and *'I thought I would find myself leaning towards cheaper prices, but the graphic imagery and warnings influenced me enough to accept paying more in return for not having them'* (Female, 21, non-smoker).

One student noted how his choices would change depending on income: *'If I took this survey back in my high school days I think I would have likely chosen the R20 cigarettes. Now that I have some money I would choose the Peter Stuyvesant packs for both questions, based only on its price'* (Male, 21, non-smoker).

Risk

Several students commented that the low price of the illicit pack led them to believe that the quality was low: *'I would have "bought" the cigarettes with the gold packaging if it had a higher price, as it is the most aesthetically appealing pack, but the low price leads one to think the quality is poor'* (Female, 23, non-smoker), and *'The higher the price, the healthier the cigarettes seem as you would think they use higher quality materials'* (Male, 19, non-smoker).

Some students noted equal risks: '*For the question which one posed the least risk to our health − I thought it was a bit strange because if you're aware of the health risks then any cigarette is bad'* (Female, 21, non-smoker).

Appeal

Two students noted that the gold packaging of the illicit pack appealed to them: *'I would most likely choose the ones I selected because of the look of the box − the gold and sophisticated look makes them more appealing'* (Female, 24, non-smoker), and '*The look of the illegal cigarette with the yellowish background, is more appealing to me as it seems to have a warmer and rounder feel to it, being supported by the description of "Gold"'* (Female, 45, non-smoker,). One student commented that the white packaging of the Peter Stuyvesant branded pack had a 'cleaner' feel: *'The use of white packaging gives a sense of cleanliness compared to the gold packaging which seems to be over-selling itself and compensating for something, increased health risk perhaps'* (Male, 32, non-smoker).

Graphic health warnings (GHW)

Many non-smokers thought that GHWs would be effective: *'As a non-smoker, I found the pictures of the very bad teeth to be very effective. Even with a really low price, I wouldn't have wanted to buy such an ugly-looking thing…It was less about me making the link between bad health and smoking, but more about just a really ugly picture that's not pleasant to look at (let alone buy!)'* (Male, 27, non-smoker), and *'I think the graphic images on the boxes are very good at deterring any interest in smoking. Visuals like that really stick with someone'* (Male, 18, non-smoker). On the other hand, some students thought that GHWs would not be effective: *'I think that the cheaper cigarette is what youngsters often start with…the packaging is the least of what attracts them to smoking'* (Male, 18, non-smoker).

The weakness of the current health warnings in South Africa (only text warnings) was emphasised in this comment: *'Words would have little to no effect on me, it is easier to ignore text than a picture'* (Female, 20, non-smoker).

A male smoker commented on that he would repackage a pack with a GHW to avoid seeing the pack: *'I am loyal to Marlboro. I will continue to purchase them even if they are the only cigarettes with the pictures on the box. I will most likely buy a cigarette holder so I don't have to look at the pictures each time I smoke. I have spent time in countries which have pictures on the box but it didn't make me smoke less'* (Male, 23, smoker).

Warnings on individual sticks

Two students thought that warnings on individual sticks was a good idea: *'...printing health warnings on cigarettes is a good idea as many cigarettes are sold loose in South Africa and thus, many people do not engage with the health warnings on the box'* (Female, 27, smoker).

One student noted that he would prefer the stick warnings to a higher price: *'…if it means saving a sufficient amount of cash, I'll gladly accept a warning on each cigarette'* (Male, 22, non-smoker). One student thought that time would desensitise people to stick warnings: *'I think that printing the caution sign on the actual cigarettes would make people feel uneasy; but after a while it'll become something they get used to (just how individuals become desensitised to the cautions on the packaging)'* (Female, 21, non-smoker).

Covid

Three students commented on the effect of Covid on purchasing behaviour: *'I think a lot of smoking preferences changed due to the restrictions during lockdown. People were forced to smoke anything, even off-brand, illegal cigarettes and this has affected their smoking behaviour after restrictions were lifted'* (Female, 32, non-smoker). One smoker commented on smoking as a means of getting outdoors: '*The 'habit' of smoking is especially hard to kick, it has now formed part of my break from work. Working from home you find that you have not stepped out of the house in two days, smoking presents an opportunity to step out and get some fresh air'* (Female, 32, smoker).

DISCUSSION

The findings from this chapter can be used to accelerate the South African CTPENDS bill that has stagnated for four years, and which among other policies includes plain packaging. The results from the DCE and the auction indicate that plain packaging is likely to reduce the demand for cigarettes.

I found that smokers reported preferring not to buy plain packs and non-smokers preferred not to try plain packs. These results are consistent with previous papers. For example, Barrientos-Gutierrez et al. (2021) found that plain packs were associated with a lower attractiveness. Babineau & Clancy (2015) found that the removal of brand identifiers, including colour, font, and embossing, reduced the perceived appeal of cigarette packs. Kotnowski et al. (2016) found that respondents would rather have tried branded packs than plain packs.

Warnings on cigarette sticks when combined with branded packs effectively reduced utility. However, when cigarette stick warnings were presented with plain packs, the effect was less. This could be because the jump from branded packs to plain packs is so large (no middle step as in most other countries) As a result, the plain pack with graphic health warning may be dominating the effect as South Africans are not used to seeing cigarette packs with GHWs and plain backgrounds. I did not test different warning messages on sticks; the only message that participants saw was ‘Smoking causes cancer’. Looking at different warnings, Drovandi et al. (2019b) (Australia) and Drovandi et al. (2019a) (Canada, the UK, the US, and Australia) found that the warning depicting the financial consequences of smoking was the most effective. Hoek et al. (2016) (New Zealand) found that a ‘minutes of life lost’ graphic had the strongest dissuasive effect relative to the other sticks tested. Moodie et al. (2020), who also only tested one message (‘Smoking kills’), found that warnings on individual cigarettes would be off-putting for young people, non-smokers and those starting to smoke.

Regarding prices, I found that smokers preferred lower-priced cigarettes to higher-priced ones, which is consistent with Giang et al. (2016). I found no evidence of a price effect among non-smokers. It was not possible to compare the price results directly with Kotnowski et al. (2016), since the authors conducted the analysis on smokers and non-smokers combined (while I analysed them separately and found different price effects according to smoking status). For smokers and non-smokers, Kotnowski et al. (2016) found that respondents would rather try lower-priced cigarettes than higher-priced cigarettes.

In terms of health risk, I found that smokers and non-smokers perceived plain packs to pose the greatest risk to health. Similarly, Harris et al. (2017) found that plain packaging was more likely to be perceived as posing a higher health risk than branded or modified branded packaging. Furthermore, Babineau & Clancy (2015) found that plain packs were perceived as less healthy than branded packs. Stick warnings (when presented with branded packs) increased the perception of risk. Smokers and non-smokers thought that cigarette packs with higher prices were less risky.

The results from the predicted probabilities indicate that smokers are more willing to buy packs with health warnings than non-smokers are. This suggests that plain packs with health warnings may be more effective in preventing smoking onset than in getting existing smokers to quit.

Using the BDM auction (completed by smokers only), I found that plain packaging decreases the WTP for cigarettes. The mean WTP for the plain pack with stick warnings (R28.10) was found to be similar to the mean WTP for the plain pack with no stick warnings (R27.60), which are both significantly less than the mean WTP for the branded pack with no stick warnings (R41.42). The lowest mean WTP is for the illicit pack at (R22.23).

Overall, these results indicate that South Africa would benefit from implementing plain packaging and health warnings on individual sticks. The delay in updating packaging laws in South Africa cannot be attributed to the cost, since the industry covers the costs of cigarette packaging. The role of the Department of Health is to determine the content of warnings, but it is the tobacco industry's task to implement and pay for the packaging. While there may be some initial costs to changing the packaging design, it is immaterial in terms of cost whether the industry is printing branded packs or plain packs. If South Africa implements plain packaging, it is likely that the manufacturers of illicit cigarettes will comply with plain packaging legislation to divert attention from their products.

Given that South Africa has eleven official languages and a high level of illiteracy, pictorial health warnings will be more effective in communicating the risks of smoking. Text warnings in South Africa have always been in English, thereby being missed out by a very significant proportion of the population who are functionally illiterate. Pictures are also important for immigrants, temporary workers, and individuals from other language groups who may not be able to read English (Canadian Cancer Society, October 2021).

While the CTPENDS bill gives some indications of what the plain packs should look like, the details still need to be developed. Section 4 of the bill states that tobacco products 'must have a uniform plain colour and texture'. The bill prescribes, among other things, that: (1) the packaging of a tobacco product must have a uniform plain colour and texture, (2) any branding, logos or other promotional elements on, inside or attached to the packaging or on an individual tobacco product are prohibited, and (3) only the brand name and product name may appear on packaging, in a standard colour and typeface, together with other mandatory information such as manufacturer's details, health warnings and tax stamps.

The bill does not state exact requirements, such as the size (percentage of the front and back) that the GHW should be, how many warnings there should be at any given time, how often the warnings should be changed, whether the GHW is also on the back of the pack, and the font size and typeface. Given this lack of any exact requirements in the bill, the DCE was designed following the Australian design (warning covering 75% of the front of the pack). Other countries, such as Benin and Nepal have warnings that cover 90% of the front of the pack (Canadian Cancer Society, October 2021), so there is nothing stopping South Africa from making the GHW larger than 75% of the pack.

The bill covers 'tobacco products', meaning that not just manufactured cigarettes will be subject to this legislation, but all tobacco products. The Australian government has published a guide on how to do this, which includes packaging for roll-you-own tobacco, cigars, and waterpipe tobacco (Australian Government: Department of Health, 2014b). Updating health warnings is also an effective way of ensuring people do not become desensitised to them. In

Australia, two sets of health warnings (each with 7 different warnings) are rotated every 12 months (Australian Government, July 2013). Keeping warnings fresh would likely reduce the 'wear-out' effect.

In three of the fourteen health warnings used in Australia, different imagery on each side is used to enhance the impact of GHWs (Australian Government, July 2013). For example, the damaged teeth and gums warning consists of a 50-year-old male smoker's damaged teeth and gums on the front, and a 45-year-old female smoker's damaged teeth and gums on the back of the pack.

Australia has also been at the frontline fighting legal battles with the tobacco industry. In June 2020, the World Trade Organization (WTO) ruled that Australia's plain packaging requirements are consistent with WTO's international trade agreements (World Trade Organization, 9 June 2020). The tobacco industry had been opposing plain packaging, arguing the measure infringed WTO trade agreements, but that argument can no longer be used.

The resistance to plain packaging dates back over a decade. In 2011, Deloitte, commissioned by BAT plc, published a 96-page report on tobacco packaging. Deloitte assessed 27 countries and covered a period of 14 years. The authors claimed that '*increasing the size of health warnings on packs and introducing graphic warnings has not directly reduced tobacco consumption – and calls into question whether plain packaging will achieve government health objectives'*. The report concluded that plain packaging would result in an increase in the illegal tobacco market, arguing that the plainer the pack, the simpler it is to counterfeit. They also argued that plain packaging would result in lost tobacco-tax revenues, and in potential legal and compensation costs for governments, and would negatively affect small retailers (Deloitte, May 2011).

When plain packaging was first placed on the agenda in South Africa, BAT South Africa threatened to close its only South African factory (BAT's eighth largest factory globally) (Business Day, 1 March 2017). A BAT spokesperson said that plain packaging threatens the future of the factory and '*poses a threat to the viability of the legal tobacco industry in SA'* (Business Day, 1 March 2017).

Surprisingly, the Fair-Trade Independent Tobacco Association (FITA), a representative body of local smaller tobacco manufacturers that compete with the South African multinational tobacco companies for market share, expressed their support for plain packaging. In November 2017, FITA released a media statement on their website stating their support of plain packaging: '*FITA encourages engagement with local manufacturers by government on the amendments, and* *whole-heartedly rejects BAT South Africa's heavy-handed bullying tactics and threats to government with regard to measures such as plain packaging. FITA, on the other hand, welcomes plain packaging'* (Fair-Trade Independent Tobacco Association, November 2017). In another press statement issued by FITA in May 2018, FITA accused BAT of opposing plain packaging '*on the spurious grounds that it will increase counterfeit and smuggled cigarettes'* (Fair-Trade Independent Tobacco Association, May 2018).

While the industry will do all they can to oppose plain packaging, the government should move ahead and ignore the threats made by the industry. By doing so, they will be putting public health first. For plain packaging to have the greatest impact, the pack needs to be seen by all smokers. If smokers have access to single cigarettes, the impact will be drastically impaired. In South Africa, a third of smokers buy their cigarettes as single sticks (Van der Zee, Van Walbeek & Magadla, 2019). While the sale of single cigarettes is illegal, the law is not enforced. For plain packaging to be most effective, the law banning single-stick sales needs to be enforced.

Single-stick sales suit the tobacco industry, as they do not lose customers who cannot afford a pack. Historical corporate documents indicate that the sale of single cigarettes, which makes smoking affordable and accessible for the poor and the young, facilitates industry expansion in Africa (Gilmore et al., 2015). Efforts to ban their sale have been contested and circumvented (Gilmore et al., 2015). Given how difficult it will be to enforce the ban on the sale of single cigarettes, it is even more important to introduce health warnings on individual sticks.

Limitations

The stated preference methodology may not uncover participants' revealed preferences and smoking behaviour following implementation of a policy that mandates plain packs or warnings on individual sticks. Moreover, the UCT student sample may not be the most appropriate sample for drawing policy prescriptions.

Peter Stuyvesant was used as the branded cigarette in the experiment as I expected this to be a popular brand amongst students. However, relatively few respondents (5%) report Peter Stuyvesant as their usual brand, suggesting that it may not be a particularly appealing choice. 52% of respondents reported Marlboro as their usual brand of choice, so perhaps Marlboro should have been used.

Informing respondents that the Caesar brand is illicit may have primed respondents, resulting in students choosing Peter Stuyvesant packs more frequently than they would have in the absence of this information. One male respondent commented: '*I was highly biased after* *learning about each cigarette brand before. If I didn't know that the cheaper ones were illegal (for example), then I may have chosen the cheaper ones'* (Male, 25, non-smoker).

By stating that these packs are illegal, the 'market' is less realistic. There are many people who do not know which cigarette packs are illicit, despite substantial media coverage on the topic in the past few years. Many students (and the actual population) may not know that cigarettes priced below a certain level are illicit, and might not buy them if they knew.

Although survey fatigue was minimised by only presenting seven choice sets to each student, students may have still experienced it. One student found the choice sets repetitive: *'I don't really see the point of asking basically the same question so many times in slightly different ways'* (Male, 32, non-smoker).

A question on smoking intensity should have been included. This could have been used to see if choices differed by smoking intensity. Perhaps smokers who smoke a pack a day have a different purchasing behaviour than smokers who smoke one cigarette a day. One student said*: 'You never asked how often I smoke.'* (Male, 22, smoker).

In the design of the experiment, the issue of trademark infringement was investigated. There was a fear that the producers of Peter Stuyvesant (British American Tobacco) and Caesar (Best Tobacco Company) might object to their brand being used in the experiment on the grounds that their trademark was being infringed. According to the Trade Marks Act 194 of 1993 (Republic of South Africa, 5 January 1994) there are three conditions that would result in the infringement of a trademark. Each of these requires that a trademark is infringed 'in the course of trade'. Since I did not trade any cigarettes, no trademark laws were infringed.

Labelling Caesar an illicit brand may elicit an objection from the producer, Best Tobacco Company. The evidence points to Caesar being an illicit brand (Van der Zee et al., 2020; Vellios & van der Zee, 2020). Caesar cigarettes are generally sold at prices that are too low to have paid excise tax (R18.39 per pack of 20 cigarettes in 2021) and value added tax (R2.76 VAT on excise per pack of 20 cigarettes in 2021). In the absence of minimum price legislation, it is possible that companies sell fully tax-paid cigarettes at a price below the price threshold to gain market share, but such a pricing strategy would be unsustainable for any length of time.

Lastly, I did not discuss the independence from irrelevant alternatives (IIA) property of conditional logit models, which implies proportionate shifting across alternatives when one alternative is removed from the choice set. This is a recognized limitation of conditional logit, and it is a reason why more flexible alternatives such as mixed logit models have become common in the discrete choice literature. Future research will investigate mixed logit models and latent class models.

CONCLUSION

The results from the DCE used in this chapter show that smokers preferred not to buy, and non-smokers preferred not to try, plain packs over branded packs. Smokers were willing to pay more for branded packs than for plain packs. Plain packaging is likely to decrease the demand for cigarettes. Smokers preferred lower prices to higher prices. This indicates that further increases in the excise tax are also likely to reduce the demand for cigarettes. Plain packaging increased the perceived risk of cigarettes.

If plain packaging is implemented in South Africa, smokers will be forced to see the effects of tobacco use every time they remove a cigarette from the pack. Non-smokers may be dissuaded from trying cigarettes. The CTPENDS bill should be implemented without further delay. Concurrently, the existing ban on the sale of single cigarettes should be enforced to ensure that smokers and non-smokers see the health warnings on plain packs.

APPENDIX

Notes for all tables:
Smokers were asked: ‘If these were the only options you had to choose from, which would you be most likely to buy?’
Non-smokers were asked: ‘If these were the only options available, which one would most likely encourage someone like you to try smoking?’
Least risk to health: Smokers & non-smokers were asked: ‘Which of these do you think would pose the least risk to your health?’

Table A1: Summary of block 1 choices

		Choice A	Choice B	Choice C	None/Other	Total
1		**PS 1**	**PS 2**	**Caesar**		
	Pack	Branded	Plain			
	Stick	No warning, branded	No warning, branded			
	Price	R48	R36	R17		
	Smokers	76 (61.3%)	11 (8.9%)	28 (22.6%)	9 (7.3%)	124 (100%)
	Non-smokers	153 (47.2%)	14 (4.3%)	130 (40.1%)	27(8.3%)	324 (100%)
	Least risk to health	282 (63.0%)	40 (8.9%)	33 (7.4%)	93 (20.8%)	448 (100%)
2		**PS 1**	**Caesar**	**PS 2**		
	Pack	Plain		Branded		
	Stick	No warning, branded		Warning, not branded		
	Price	R48	R20	R48		
	Smokers	11 (8.9%)	43 (34.7%)	57 (46.0%)	13 (10.5%)	124 (100%)
	Non-smokers	29 (8.6%)	179 (55.3%)	91 (28.1%)	26 (8.0%)	324 (100%)
	Least risk to health	68 (15.2%)	99 (22.1%)	185 (41.3%)	96 (21.4%)	448 (100%)
3		**Caesar**	**PS 1**	**PS 2**		
	Pack		Plain	Branded		
	Stick		Warning, not branded	Warning, not branded		
	Price	R20	R36	R48		
	Smokers	49 (39.5%)	16 (12.9%)	49 (39.5%)	10 (8.1%)	124 (100%)
	Non-smokers	196 (60.5%)	15 (4.6%)	87 (26.9%)	26 (8.0%)	324 (100%)
	Least risk to health	131 (29.2%)	38 (8.5%)	189 (42.1%)	90 (20.1%)	448 (100%)
4		**PS 1**	**PS 2**	**Caesar**		
	Pack	Branded	Plain			
	Stick	Warning, not branded	No warning, branded			
	Price	R36	R36	R17		
	Smokers	65 (52.4%)	9 (7.3%)	37 (29.8%)	13 (10.5%)	124 (100%)
	Non-smokers	108 (33.3%)	12 (3.7%)	176 (54.3%)	28 (8.6%)	324 (100%)
	Least risk to health	189 (42.3%)	57 (12.8%)	113 (25.3%)	88 (19.7%)	448 (100%)
5	(Choice set with dominant choice)					
6		**PS 1**	**Caesar**	**PS 2**		
	Pack	Plain		Branded		
	Stick	Warning, not branded		No warning, branded		
	Price	R36	R17	R40		
	Smokers	8 (6.5%)	32 (25.8%)	75 (60.5%)	9 (7.3%)	124 (100%)
	Non-smokers	16 (4.9%)	132 (40.7%)	151 (46.6%)	25 (7.7%)	324 (100%)
	Least risk to health	45 (10.0%)	46 (10.3%)	272 (60.7%)	85 (19.0%)	448 (100%)
7		**PS 1**	**PS 2**	**Caesar**		
	Pack	Branded	Plain			

	Stick	No warning, branded	Warning, not branded			
	Price	R48	R44	R20		
	Smokers	72 (58.1%)	9 (7.3%)	35 (28.2%)	8 (6.5%)	124 (100%)
	Non-smokers	144 (44.4%)	11 (3.4%)	145 (44.8%)	24 (7.4%)	324 (100%)
	Least risk to health	267 (59.6%)	49 (10.9%)	47 (10.5%)	85 (19.0%)	448 (100%)

Table A2: Summary of block 2 choices

		Choice A	**Choice B**	**Choice C**	**None/Other**	**Total**
1		**PS 1**	**Caesar**	**PS 2**		
	Pack	Plain		Branded		
	Stick	Warning, not branded		Warning, not branded		
	Price	R44	R17	R48		
	Smokers	12 (9.8%)	45 (36.9%)	47 (38.5%)	18 (14.8%)	122 (100%)
	Non-smokers	14 (4.1%)	172 (50.4%)	123 (36.1%)	32 (9.4%)	341 (100%)
	Least risk to health	53 (11.5%)	87 (18.8%)	211 (45.6%)	112 (24.2%)	463 (100%)
2		**PS 1**	**PS 2**	**Caesar**		
	Pack	Plain	Branded			
	Stick	Warning, not branded	No warning, branded			
	Price	R36	R40	R20		
	Smokers	8 (6.6%)	73 (59.8%)	30 (24.6%)	11 (9.0%)	122 (100%)
	Non-smokers	8 (2.4%)	146 (42.8%)	155 (45.5%)	32 (9.4%)	341 (100%)
	Least risk to health	51 (11.0%)	252 (54.4%)	60 (13.0%)	100 (21.6%)	463 (100%)
3		**Caesar**	**PS 2**	**PS 1**		
	Pack		Branded	Branded		
	Stick		Warning, not branded	No warning, branded		
	Price	R17	R36	R48		
	Smokers	31 (25.4%)	40 (32.8%)	40 (32.8%)	11 (9.0%)	122 (100%)
	Non-smokers	154 (45.2%)	46 (13.5%)	112 (32.8%)	29 (8.5%)	341 (100%)
	Least risk to health	56 (12.1%)	72 (15.6%)	241 (52.1%)	94 (20.3%)	463 (100%)
4		**PS 1**	**PS 2**	**Caesar**		
	Pack	Plain	Plain			
	Stick	No warning, branded	Warning, not branded			
	Price	R48	R44	R17		
	Smokers	15 (12.3%)	17 (13.9%)	69 (56.6%)	21 (17.2%)	122 (100%)
	Non-smokers	27 (7.9%)	13 (3.8%)	266 (78.0%)	35 (10.3%)	341 (100%)
	Least risk to health	81 (17.5%)	54 (11.7%)	230 (49.7%)	98 (21.2%)	463 (100%)
5	(Choice set with dominant choice)					
6		**PS 1**	**PS 2**	**Caesar**		
	Pack	Branded	Plain			
	Stick	Warning, not branded	No warning, branded			
	Price	R36	R36	R20		
	Smokers	55 (45.1%)	8 (6.6%)	48 (39.3%)	11 (9.0%)	122 (100%)
	Non-smokers	81 (23.8%)	8 (2.4%)	219 (64.2%)	33 (9.7%)	341 (100%)
	Least risk to health	147 (31.8%)	66 (14.3%)	158 (34.1%)	92 (19.9%)	463 (100%)
7		**Caesar**	**PS 1**	**PS 2**		
	Pack		Plain	Plain		
	Stick		Warning, not branded	No warning, branded		
	Price	R20	R44	R48		
	Smokers	71 (58.2%)	19 (15.6%)	14 (11.5%)	18 (14.8%)	122 (100%)

	Non-smokers	257 (75.4%)	20 (5.9%)	24 (7.0%)	40 (11.7%)	341 (100%)
	Least risk to health	225 (48.6%)	55 (11.9%)	90 (19.4%)	93 (20.1%)	463 (100%)

Table A3: Summary of block 3 choices

		Choice A	Choice B	Choice C	None/Other	Total
1		**PS 1**	**PS 2**	**PS 3**		
	Pack	Plain	Branded	Plain		
	Stick	No warning, branded	Warning, not branded	Warning, not branded		
	Price	R52	R52	R48		
	Smokers	11 (9.0%)	78 (63.9%)	17 (13.9%)	16 (13.1%)	122 (100%)
	Non-smokers	13 (3.7%)	279 (79.9%)	18 (5.2%)	39 (11.2%)	349 (100%)
	Least risk to health	64 (13.6%)	239 (50.7%)	24 (5.1%)	144 (30.6%)	471 (100%)
2		**PS 1**	**PS 2**	**PS 3**		
	Pack	Branded	Plain	Branded		
	Stick	Warning, not branded	No warning, branded	No warning, branded		
	Price	R32	R32	R52		
	Smokers	69 (56.6%)	8 (6.6%)	35 (28.7%)	10 (8.2%)	122 (100%)
	Non-smokers	117 (33.5%)	14 (4.0%)	190 (54.4%)	28 (8.0%)	349 (100%)
	Least risk to health	53 (11.3%)	39 (8.3%)	132 (28.0%)	132 (28.0%)	471 (100%)
3		**PS 1**	**PS 2**	**PS 3**		
	Pack	Branded	Plain	Plain		
	Stick	Warning, not branded	No warning, branded	Warning, not branded		
	Price	R52	R52	R32		
	Smokers	69 (56.6%)	11 (9.0%)	26 (21.3%)	16 (13.1%)	122 (100%)
	Non-smokers	265 (75.9%)	24 (6.9%)	18 (5.2%)	42 (12.0%)	349 (100%)
	Least risk to health	253 (53.7%)	75 (15.9%)	21 (4.5%)	122 (25.9%)	471 (100%)
4		**PS 1**	**PS 2**	**PS 3**		
	Pack	Branded	Branded	Plain		
	Stick	Warning, not branded	No warning, branded	No warning, branded		
	Price	R32	R36	R32		
	Smokers	37 (30.3%)	73 (59.8%)	5 (4.1%)	7 (5.7%)	122 (100%)
	Non-smokers	74 (21.2%)	239 (68.5%)	8 (2.3%)	28 (8.0%)	349 (100%)
	Least risk to health	47 (10.0%)	260 (55.2%)	43 (9.1%)	121 (25.7%)	471 (100%)
5	(Choice set with dominant choice)					
6		**PS 1**	**PS 2**	**PS 3**		
	Pack	Plain	Branded	Branded		
	Stick	Warning, not branded	Warning, not branded	No warning, branded		
	Price	R44	R48	R52		
	Smokers	17 (13.9%)	43 (35.3%)	48 (39.3%)	14 (11.5%)	122 (100%)
	Non-smokers	12 (3.4%)	95 (27.2%)	214 (61.3%)	28 (8.0%)	349 (100%)
	Least risk to health	30 (6.4%)	49 (10.4%)	271 (57.4%)	121 (25.7%)	471 (100%)
7		**PS 1**	**PS 2**	**PS 3**		
	Pack	Branded	Plain	Plain		
	Stick	No warning, branded	No warning, branded	Warning, not branded		
	Price	R40	R36	R32		
	Smokers	84 (68.9%)	8 (6.6%)	21 (17.2%)	9 (7.4%)	122 (100%)
	Non-smokers	301 (86.3%)	8 (2.3%)	15 (4.3%)	25 (7.2%)	349 (100%)
	Least risk to health	294 (62.4%)	27 (5.7%)	34 (7.2%)	116 (24.6%)	471 (100%)

Table A4: The two choice sets with dominant choice

	Option A	Option B	Option C	None / Other	Total
Blocks 1 and 2					
			Dominant choice		
Pack	Plain	Illicit	Branded		
Stick	Warning, no branding		No warning, branding		
Price	R40	R20	R36		
Smokers	3 (1.2%)	52 (21.1%)	174 (70.7%)	17 (6.9%)	246 (100%)
Non-smokers	30 (4.5%)	279 (42.0%)	301 (45.3%)	55 (8.3%)	665 (100%)
Least risk to health	137 (15.0%)	111 (12.2%)	488 (53.6%)	175 (19.2%)	911 (100%)
Block 3					
		Dominant choice			
Pack	Plain	Branded	Plain		
Stick	Warning, no branding	No warning, branding	No warning, branding		
Price	R52	R44	R48		
Smokers	5 (4.1%)	104 (85.3%)	1 (0.8%)	12 (9.8%)	349 (100%)
Non-smokers	18 (5.2%)	300 (86.0%)	4 (1.2%)	27 (7.7%)	122 (100%)
Least risk to health	51 (10.8%)	275 (58.4%)	31 (6.6%)	114 (24.2%)	471 (100%)

CHAPTER 4: Illicit Cigarette Trade in South Africa: 2002–2017

INTRODUCTION

South Africa has to date (May 2022) failed to adopt the best international practices in tax administration. It uses a simple and barely visible imprint of a diamond-shaped stamp to mark cigarette packs destined for the domestic market. The tax authority has little control over the use of the diamond stamp impression, which is easy to counterfeit and impossible to verify. There is no link between tax payment and the diamond stamp impression.

Other pack features that are meant to indicate lawfulness include: (1) health warnings, (2) the presence of a quit line telephone number, (3) tar and nicotine readings which may not be higher than 12 mg for tar or 1.2 mg for nicotine, and (4) the words 'Reduced Ignition Propensity' printed on the side of the pack (Republic of South Africa, 1995; Republic of South Africa: Department of Health, 16 May 2011; Republic of South Africa: Department of Health, 29 September 2000). As with the diamond stamp, the presence of these features does not mean that a pack is legal.

While some researchers (Maldonado et al., 2018; Ross et al., 2019) have used cigarette packs to estimate the size of illicit trade, examining packs to determine lawfulness is not feasible in South Africa. This method can only be used in countries where pack features (specifically excise tax stamps but also other features such as the correct health warnings) are reliable determinants of whether or not a pack is legal. In Colombia, 1697 smokers were interviewed, and interviewees examined their cigarette packs (Maldonado et al., 2018). In Mongolia, 19 000 discarded cigarette packs were collected to assess the size of the illicit market (Ross et al., 2019).

'Illicit trade' is an umbrella term that encompasses many illegal activities. The WHO's FCTC defines illicit trade as 'any practice or conduct prohibited by law and which relates to production, shipment, receipt, possession, distribution, sale or purchase, including any practice or conduct intended to facilitate such activity' (World Health Organization, 2003). Table 4.1 provides a list of illicit trade terms with their definitions, together with examples and whether or not these types of illicit trade are problematic in South Africa.

Tax avoidance refers to legal activities to pay less tax or no tax. Tax avoidance undermines the effectiveness of excise taxes as people who may have quit (or not started) have access to cheap cigarettes. It is unlikely that there is much tax avoidance in South Africa from cross-border shopping, since cigarette prices in neighboring countries are either similar to those in South Africa or higher, as a result of a common excise tax in the Southern African Customs

Union (South Africa, Botswana, Lesotho, Namibia and Swaziland) (Blecher & Drope, 2014). Other forms of tax avoidance in South Africa are minimal. The only duty-free shops are found at airports. Internet purchases of cigarettes are also not common in South Africa. For example, Makro, a major retailer, states on its website that cigarettes can be bought in-store only. Other popular online retailers, such as TakeAlot, do not sell cigarettes.

Table 4.1: Illicit trade terms

Term	**Definition***	**Examples**	**Problematic in South Africa**
Tax avoidance	Legal activities to pay less tax or no tax	Consumers buy cigarettes from lower tax jurisdictions in the allowed quantities; duty-free shopping; internet purchases (in jurisdictions where internet sales are allowed); changing products' characteristics	No
Tax evasion	Illegal activities to pay less or no tax	No excise tax paid to government (undeclared production)	Yes
Smuggling	The illegal trading of products across borders	Bringing cigarettes from Botswana to South Africa in larger quantities than legally allowed	Likely
Counterfeit production	Production of manufactured products which bear a trademark without the consent of the owner of the trademark	Manufacturing cigarettes which bear the Peter Stuyvesant trademark without permission from British American Tobacco	Unlikely

**Source: Joossens, L. & Raw, M. 2012. From cigarette smuggling to illicit tobacco trade. Tobacco Control. 21(2):230-234. DOI:10.1136/tobaccocontrol-2011-050205.*

Tax avoidance can also occur when manufacturers' change the characteristics of products. Since South Africa's excise regime is one of a specific uniform tax, tobacco manufacturers are not in a position to change their products' characteristics in order to reduce their tax liability. The same amount of excise tax is levied per pack of 20 cigarettes, regardless of features such as cigarette length, cigarette circumference, hard/soft pack, or filter/non-filter.

Tax evasion refers illegal activities to pay less or no tax. Tax evasion is a significant issue in South Africa, which is acknowledged by both the tobacco industry and independent researchers (Kahn, 26 May 2018) (Tobacco Institute of Southern Africa, 2016). The current illicit cigarette market is dominated by 'genuine' illicit cigarettes, i.e. production is not declared to the South African Revenue Service (SARS) (Haysom, March 2019).

Smuggling refers to the illegal trading of cigarettes across borders. The exact scale of the smuggling and the number of cigarettes smuggled in South Africa is unknown. Cigarettes produced in Zimbabwe are smuggled into all its neighboring countries, with the majority smuggled into South Africa (Haysom, March 2019).

Counterfeited cigarettes are packaged with branding identical or near-identical to popular cigarette brands (typically the premium brands made by multinationals). Tax is not paid on these products. Counterfeiting was prevalent in South Africa in the 1990s, but its incidence was eclipsed, though not entirely eliminated, by under-declaration in the 2000s (Haysom, March 2019).

The aim of this chapter is to provide independent estimates of illicit trade (specifically tax evasion) in South Africa from 2002 to 2017 using gap analysis. While the gap analysis largely captures tax evasion, it may also capture some tax avoidance (for example, smokers buying cigarettes at duty free shops at airports). Gap analysis is one of several methods used to measure the size of the illicit cigarette market (Ross, 2015). It is based on a comparison of consumption estimates (from survey data) with legitimate sales (as declared to the excise tax authority). The gap between self-reported consumption (scaled up to account for under-reporting) and legitimate sales is an indication of the size of the illicit market.

Estimates of illicit trade in the current study were compared to existing independent studies, and those produced by the tobacco industry. The discussion section explores how the management crisis at SARS impacted the illicit trade market.

LITERATURE REVIEW

Existing estimates of illicit trade in South Africa

Illicit trade in South Africa has been measured using various approaches. These studies have been done by both independent researchers and the tobacco industry. While measures of illicit trade were contentious in the past (the tobacco industry estimates were higher than those of independent researchers), estimates in recent years have converged.

1. Estimates from independent researchers

To measure illicit trade in 2017, Van der Zee et al. (2020) used the price threshold method, which distinguishes tax-paid cigarettes from non-tax paid cigarettes. The authors used a sample of 4224 smokers from the fifth wave of the 2017 National Income Dynamics Study (NIDS). A price threshold of R20 (1.50 USD) or less was based on the cost of a legal pack that included taxes, production costs, and profits. Van der Zee et al. (2020) estimated illicit trade to be 31%. Smokers who are White or Coloured, older, less educated and lower income were more likely to buy illicit cigarettes.

A subsequent 2020 publication investigated the illicit cigarette market in six South African townships (Van der Zee et al., 2020), also using the price threshold method. Data was collected in 2017 and 2018 from townships, which are underdeveloped and segregated urban areas that are spatially disconnected from economic centres, often located on the outskirts of major metropolitan areas. Smokers (n=1234 in round 1 and n=1193 in round 2) were asked about their most recent cigarette purchase. Cigarettes purchased for R1 (US$0.08) or less per stick were presumed to be illicit. In 2017 and 2018 respectively, 35% and 36% of smokers in the sample purchased illicit cigarettes (the increase was not statistically significant. Smokers with relatively low socioeconomic status, those who had low levels of education, and those who were older or unemployed were most likely to purchase illicit cigarettes (Van der Zee et al., 2020).

Van Walbeek (2014) compared the change in legal cigarette sales to the predicted change in total (legal and illicit) consumption to quantify changes in the illicit cigarette market from 1995 to 2012 (Van Walbeek, 2014). Given that the cigarette demand in South Africa is unusually strongly and predictably influenced by income (GDP) and cigarette prices, he was able to predict total cigarette consumption, using a time series regression model. He found that predicted total cigarette consumption was highly correlated with the change in legal consumption, and thus concluded that illicit cigarette trade had not increased between 2002 and 2009 (Van Walbeek, 2014). However, there was a substantial spike in 2010.

Using a gap analysis method, Blecher (2010) estimated the size of the illicit market to be 9.4% to 11.5% of the total market in 2000 and 7% to 11.2% in 2007. Blecher (2010) is discussed in further detail in the gap analysis literature review section.

2. Estimates from South African Revenue Service (SARS)

In a 2014 presentation, SARS reported that 29% of the total cigarette market consisted of illegal cigarettes (South African Revenue Service, 19 August 2014). The methodology was not described in the presentation. In October 2019, SARS announced that it was estimating the size of the illicit economy (including other illicit activities, such as illicit mining of gold and diamonds, ivory smuggling, and the poaching of endangered species), and that the results would be available in March 2020 (Business Day, 14 October 2019). To date (May 2022), no results have been released to the public.

3. Estimates from Euromonitor International

Euromonitor International, a market research firm that sells data on a variety of consumer goods, provides data and information on production, trade, sales, brands, illicit trade, and the competitive landscape of cigarettes in various countries. Although Euromonitor International provides illicit trade data, these estimates have been called into question by independent researchers. Blecher (2010) analysed Euromonitor International's data on illicit cigarette trade in South Africa. He looked at three editions of Euromonitor International's reports on South Africa (2002, 2005, and 2007). Estimates of illicit trade in these three reports differ significantly. For example, the 2002 report stated that illicit trade was 28.4% in 2000, while the 2005 report stated that illicit trade was 1.9% in 2000. In a later publication, Blecher et al. (2015) concluded that estimates for Mexico were also unreliable.

In March 2019, Euromonitor International received funding from two initiatives solely-funded by Philip Morris International: the Foundation for a Smoke-Free World and PMI IMPACT. In April 2019 academics publicised that Euromonitor International had received money from the tobacco industry and Euromonitor International were heavily criticised for it (Gallagher & Gilmore, 8 April 2019). Euromonitor International's association with the tobacco industry resulted in them losing credibility with independent researchers. Many organisations cancelled their subscriptions. In January 2020, the Campaign for Tobacco-Free Kids circulated an email to the tobacco control community announcing that: 'In 2019 the Campaign stopped our subscription with Euromonitor International after learning that the company had entered into a partnership with PMI on a project that will further PMI's business strategy' (Campaign for Tobacco-Free Kids, 27 January 2020). In the same email thread, a senior policy advisor from the Southeast Asia Tobacco Control Alliance (SEATCA) noted that they also had cancelled their Euromonitor International subscription in 2019.

4. Estimates from the tobacco industry

Recent and historical estimates of illicit trade from the tobacco industry were provided by the now-defunct Tobacco Institute of Southern Africa (TISA). TISA represented the multinationals, tobacco processors, and farmers. In December 2019, TISA announced that 'it is to wind up its operations' and that 'its members have taken a decision to redeploy their resources to fulfil their individual strategic objectives' (Tobacco Institute of South Africa, 2019).

In 2018, TISA commissioned market-research firm Ipsos to measure illicit trade in South Africa, over two rounds of data collection. Ipsos defined illicit cigarettes as those priced below R17.85 per pack, which was the excise tax and value-added tax (VAT) applicable in 2018 (about $1.30 in October 2018) (Ipsos, 2018a). Aside from describing the threshold price methods, descriptions of other methods (for example how the sample was selected) were scanty. In the first round (June 2018), Ipsos audited 2058 independent retail outlets in South Africa (Ipsos, 2018a) and found that 27% of the cigarette market in SA was illicit (Van Rensburg, 8 July 2018). In the second round (September 2018), using the same sample, Ipsos found that the illicit market had grown to 33% of the total cigarette market (Ipsos, 2018b). TISA used the results of the Ipsos study to run a comprehensive #TakeBackTheTax campaign, in which they called on the government to curb illicit trade.

Ipsos reported that smaller local manufacturers were the producers of the illicit brands. Gold Leaf Tobacco Company was publicly identified as the major producer of these cigarettes (Ipsos, 2018a; Ipsos, 2018b). This is not surprising given that TISA was an industry group for the multinationals, in competition with the local tobacco industry.

Ipsos was subject to considerable criticism for not disclosing the methods (Van Dyk, 7 September 2018). Francois van der Merwe (the then TISA Chairperson) argued that the information was TISA's property, no formal report had been written, and the raw data would be open to misinterpretation (Van Dyk, 7 September 2018). Neither IPSOS nor TISA allowed Bhekisisa (the news outlet) to see the written methods of the survey (Van Dyk, 7 September 2018).

Earlier estimates of illicit trade were also provided by TISA, who retrospectively adjusted illicit trade estimates to fit the narrative that illicit trade was increasing sharply. For example, in a 2012 presentation to National Treasury, TISA claimed that the 2008 illicit market share was 8%, in contrast with its earlier claim (made in 2008 and 2009) that the illicit market share was 20% in that year (Van Walbeek, 2014). The methods of how these estimates were calculated is not shared publicly.

The tobacco industry's lack of transparency and inconsistent estimates is not unique to South Africa. (Gallagher et al., 2018) analysed global tobacco industry data on illicit trade and concluded that industry data are unreliable.

5. Funding unclear (Lemboe and Black, 2012)

Lemboe and Black's working paper (2012) compared legal sales with estimated cigarette consumption from 2001 to 2008 using the All Media and Products Survey and estimated the illicit market share to reach up to 40−50% (Lemboe & Black, 2012). However, these results were based on a misleading assumption that those who reported smoking 11 or more cigarettes per day consumed on average 55 cigarettes per day (Lemboe & Black, 2012). Using data from the 2008 National Income Dynamics Survey, I found that 'heavy smokers' consumed on average 19.9 cigarettes per day. Anecdotal evidence indicates that one of the authors of this study (Black) conducted extensive research for the tobacco industry in the past.

Gap analysis literature review

Gap analysis is a method used to measure illicit trade. Legal cigarette sales (tax-paid consumption) are compared to consumption reported in surveys (self-reported consumption). Legal cigarette sales data are obtained from government statistics or from the tobacco industry, while consumption estimates are obtained from national surveys that ask respondents about their smoking habits (whether or not they smoke and if a smoker, how many cigarettes they smoke). The full explanation of the gap analysis methodology is provided in the *methods and data* section.

Gap analyses have been done in South Africa (Blecher, 2010), five South American countries (Argentina, Brazil, Chile, Colombia, and Peru) (Paraje, 2018), Canada (Guindon, Burkhalter & Brown, 2017; Physicians for a Smoke-Free Canada, 2013), the UK (Her Majesty's Revenue and Customs, 14 June 2018), the USA (Stehr, 2005), and Vietnam (Nguyen et al., 2014). While there are two further papers on Chile (Debrott Sánchez, 2006; Jorratt M, 2012) and Uruguay (Ramos & Curti, 2006) (which are mentioned in Paraje 2018), they are not in English. Debrott Sánchez (2006) is briefly described since it was discussed in Paraje (2018).

South Africa

Blecher (2010) estimated illicit trade in South Africa from 1997 to 2007. He used several sources of data: Van Walbeek (2005), the All Media and Products Survey (AMPS), Euromonitor International, and Statistics South Africa's (Stats SA) mid-year population estimates. Blecher did not have the raw AMPS data, but instead obtained aggregated data. Subsequently, raw AMPS data (2001 – 2015) were purchased from the South African Advertising Research Foundation (SAARF) and is now publicly available to researchers through DataFirst, a data repository managed by the University of Cape Town.

Since Blecher (2010) did not have reliable and consistent smoking intensity data prior to 2001 (AMPS asked respondents whether they were light, medium, or heavy smokers), he simulated smoking intensity based on anecdotal evidence of declining smoking intensity from 1997 to 2007. The simulation approach relied on two point estimates of smoking intensity: (1) 4053 cigarettes per smoker per year in 1997, and (2) 3176 cigarettes per smoker per year in 2007. Smoking intensity estimates for the years between 1997 and 2007 were calculated as a function that decreased at a decreasing rate. He specified a decaying factor in the simulation model to achieve a specific outcome in 2007 (3176 cigarettes). In addition to these estimates, Blecher (2010) accounted for under-reporting by scaling up the consumption estimates by 5% and 10% (he presented all three estimates).

For the first point estimate, Blecher (2010) used data on *legal consumption* from Van Walbeek (2005). Van Walbeek (2005) calculated legal consumption by taking the total excise revenue and dividing it by the specific excise tax. From this data, Blecher (2010) calculated smoking intensity of the legal market. Blecher (2010) then used Euromonitor International data on the *total market* to calculate smoking intensity. In 1997, the data from Van Walbeek (2005) and Euromonitor International were close, implying little to no illicit trade. For this reason, Blecher (2010) used Van Walbeek's data as the starting point in 1997. This assumption implies that the legal market is equal to the total market. For the second point estimate for the year 2007, Blecher (2010) used AMPS data, which asked respondents how many cigarettes they smoked the previous day.

The results for smoking intensity for the years for which there was continuous smoking-intensity data (2001 – 2007) were similar to the simulated results. Blecher (2010) concluded that the size of the illicit market grew substantially from 1997 until peaking in 2000 at an estimated 9.4% − 11.5% of the total market. In 2007, he estimated illicit trade to be 7.0% − 11.2% of the total market.

Blecher (2010) did not account for imports in his estimation of tax-paid sales, as he erroneously assumed that excise tax from imports are included under the budget line 'Cigarettes and cigarette tobacco' in the national accounts (Republic of South Africa: National Treasury). Excise tax received from imported cigarettes is captured as part of budget line 'Miscellaneous customs and excise receipts'. If he had included imports, his estimates of illicit trade would have been lower, since the gap between tax-paid sales and self-reported consumption would have been narrower.

Argentina, Brazil, Chile, Colombia, and Peru

Paraje (2018) selected Argentina, Brazil, Chile, Colombia, and Peru for his study on the size of the illicit market, as these were the only countries in South America that have two or more waves of nationally representative surveys that included questions on smoking. Two or more surveys are necessary to compare trends over time for any country. From the various national surveys, he extracted data on the total population, smoking prevalence, and smoking intensity (number of cigarettes smoked per day).

For Argentina, Paraje (2018) used registered cigarette consumption data from the Ministry of Agro-industry, while for Brazil he used registered cigarette sales from the Federal Revenues Service. Imported cigarettes were included in the sales data for Argentina and Brazil. Since there was no official information on registered sales for Chile, Colombia, and Peru, Paraje

(2018) used sales information from Euromonitor International. Paraje (2018) argued that while Euromonitor International's data on illicit trade is unreliable, their data on sales is not.

Paraje (2018) did not make any assumptions about the level of under-reporting, but assumed that under-reporting was consistent over time. This allowed him to compare *trends* in illicit trade over time, but not to assess the *size* (percentage) of the illicit cigarette market.

Paraje (2018) found that illicit trade increased in Brazil (2008 – 2013), but found no evidence of an increase in illicit trade in Chile (2008 – 2014), Colombia (2008 – 2013), or Peru (2006 – 2010). For Argentina, there was a relative decrease in the illicit market from 2005 to 2009, stabilising thereafter. As a sensitivity analysis, Paraje (2018) used sales information data from Euromonitor International for Argentina and Brazil instead of official data. For Argentina and Brazil, the results were robust, but for Brazil the increase in illicit trade was smaller when Euromonitor International data were used.

The conclusion in Paraje (2018), that illicit trade increased in Brazil, is consistent with Iglesias et al. (2017), who used a different method (price threshold method) to estimate illicit trade. To establish a boundary between legal and illegal cigarettes, Iglesias et al. (2017) defined a threshold price consisting of: (1) production and distribution costs of a cheap brand, (2) excise and other taxes, and (3) retail margins per pack, but without any net profit margin for the manufacturer. Using price data from two representative surveys, Iglesias et al. (2017) estimated that the total proportion of illicit daily consumption increased from 17% to 31% between 2008 and 2013.

Like Paraje (2018), Szklo et al. (2018) also used a gap analysis to estimate illicit cigarette consumption in Brazil from 2012 to 2016, but used different data for self-reported consumption: Szklo et al. (2018) used self-reported consumption data from an annually conducted telephone survey, while Paraje (2018) used the 2018 Global Adult Tobacco Survey and a 2013 National Health Survey. The authors of both papers used legal sales data from the Secretariat of Federal Revenues.

Szklo et al. (2018) estimated under-reporting in Brazil, using Iglesias et al. (2017) estimate of illegal consumption. In any gap analysis, the gap between tax-paid sales and self-reported consumption consists of both illicit trade and under-reporting. If illicit trade is known in a particular year (in this case 2013), then the degree of under-reporting can be estimated. Szklo et al. (2018) assumed that under-reporting was constant over the analysis period.

Szklo et al. (2018) were the first authors to stratify under-reporting; all other authors used one level of under-reporting for the full sample. Szklo et al. (2018) stratified under-reporting by educational level (< 8 years vs ≥ 8 years) to account for 'the likely differential information bias related to conducting phone surveys across different socioeconomic status groups'. The authors estimated that under-reporting was 88% among individuals with lower levels of education and 82% for individuals with higher levels of education.

These unusually high levels of under-reporting were confirmed via email correspondence with the main author (Personal communication with André Szklo, 8 May 2020). He explained that very high values for the under-reporting were used because the phone survey only captured individuals aged 18 years and older living in Brazilian state capitals and, therefore, only represented 27% of the total adult urban population, 24% of the country´s total adult population, and 18% of the smoking population (for year 2013) (Personal communication with André Szklo, 8 May 2020). To account for smokers being under-represented, under-reporting levels were therefore very high. As official legal sales were not provided by educational level, the authors used the percentage distribution of legal cigarette consumption by educational level from 2013 GATS-Brazil survey 2013 to obtain the estimates of legal sales for the two levels of education. The authors found that the estimated proportion of illicit cigarette used in Brazil increased from 29% in 2012 to 43% in 2018.

Canada

Guindon, Burkhalter & Brown (2017) measured trends in illicit trade in Canada from 1999 to 2013 using two approaches. First, they contrasted estimates of tax-paid cigarette sales with consumption estimates from survey data (gap analysis). This is an updated and improved analysis of an earlier unpublished report by an NGO (Physicians for a Smoke-Free Canada, 2013).

Second, the authors used responses to survey questions relevant to purchases from First Nation Reserves. In Canada, illicit cigarettes are typically cigarettes sold on First Nation Reserves or through networks operating off-reserves, without the collection of federal and provisional taxes.

As well as looking at Canada at a national level, the authors also focused on Ontario and Québec since a large proportion of illicit cigarettes are believed to originate from reserves on the borders of these two provinces (Guindon, Burkhalter & Brown, 2017).

As a measure of tax-paid sales, Guindon, Burkhalter & Brown (2017) used cigarette sales data, as reported by tobacco manufacturers to Health Canada (the government department responsible for national public health). Guindon, Burkhalter & Brown (2017) estimates of tax-paid sales included imported cigarettes. The authors calculated self-reported cigarette consumption using data from two large national surveys.

Guindon et al. (2017) presented trends in the illicit trade market in Quebec, Ontario, and Canada for 1999 to 2013 (Guindon, Burkhalter & Brown, 2017). The authors also presented estimates for illicit trade in Ontario using under-reporting levels of 35% and 40%. These levels were chosen as self-reported consumption represented about 65% and 60% of tax-paid consumption, depending on the dataset used (Guindon, Burkhalter & Brown, 2017).

The authors found a clear upward trend from the early 2000s in cigarette contraband in Québec and Ontario followed by, on the whole, a decreasing trend from about 2007 to 2009.

United Kingdom

Her Majesty's Revenue and Customs (HMRC) measures tax gaps (the difference between the amount of tax that should be paid to HMRC, and what is actually paid) for all types of taxes. These include VAT, excise (for alcohol, tobacco, hydrocarbon oils, and other excise taxes), corporation tax and income tax, National Insurance Contributions, and Capital Gains Tax (Her Majesty's Revenue and Customs, 20 June 2019). Annual reports have been published since 2010 and are available online.

HMRC calculates the tax gap for both cigarettes and hand-rolled tobacco. HMRC calculates both the size of and the trends in the illicit cigarette market. HMRC estimates total consumption using the General Lifestyle Survey, the Opinions and Lifestyle Survey, and the Health Survey for England. Estimates of the adult population (16+) are obtained from the Office for National Statistics. Estimates of legitimate consumption include UK duty-paid consumption, and legal cross-border and duty-free shopping. Data on UK duty-paid consumption is taken directly from HMRC tax returns from cigarette manufacturers, which include both volumes of cigarettes and actual amounts of money. The estimate of the volume of cross-border and duty-free shopping are derived from the International Passenger Survey. Legitimate consumption is subtracted from total consumption; the residual is estimated to be the illicit market.

HMRC uses an 'uplift factor' to account for under-reporting. To quantify the under-reporting bias, the uplift factor is calculated by dividing total legitimate (i.e. tax-paid) consumption by total self-reported consumption in a year when illicit trade is believed to be negligible (in which case under-reporting is the only unknown variable). The uplift factor is applied to self-reported consumption to upscale the estimates in subsequent years (Her Majesty's Revenue and Customs, 14 June 2018). Since the exact value of the uplift factor is not specified in the reports, I sent a Freedom on Information request to HMRC, who promptly replied that an uplift factor of 1.46 is applied to cigarettes in all years (Her Majesty's Revenue and Customs, 5 March 2020). This implies that 100 self-reported cigarettes are increased to 146 actual cigarettes. Therefore, the survey was able to capture 68.5% of smokers' consumption (x=100/146). The assumption is that under-reporting is 31.5% (100%−68.5%).

HMRC estimated that the illicit cigarette market was 16% in 2005/06, decreasing to 8% in 2014/15, increasing to 15% in 2016/17 and then decreasing again to 9% in 2017/18 (Her Majesty's Revenue and Customs, 20 June 2019). HMRC estimates that the *tobacco* tax gap in 2017/2018 accounted for a revenue loss of £1.8 billion. The *cigarette* tax gap is estimated to be £1 billion and the *hand-rolling tobacco* tax gap is estimated to be £0.8 billion. The tobacco tax gap of £1.8 billion can be decomposed into losses due to evasion of tobacco duties (£1.4 billion) and losses due to evasion of VAT (£0.4 billion).

United States

To investigate illicit trade in the US from 1985–2001, Stehr (2005) used several methods, one of which was a gap analysis. Although Stehr (2005) used the term 'tax avoidance' to encompass both legal tax avoidance and illegal tax evasion, I will refer to what he calls 'tax avoidance' as 'illicit trade', as this is a more accurate term, and is consistent with the recent literature.

Cigarette consumption and demographic data were drawn from the 1984 to 2001 Behavioral Risk Factor Surveillance System. Cigarette tax and per capita tax-paid sales data for 1985–2001 were sourced from the 2003 *Tax Burden on Tobacco* report, published by economic consultancy firm Orzechowski and Walker, which has produced the report since 1989. The 2014 report (the latest report available) states that it was prepared with the financial support of Altria Client Services, the Lorillard Tobacco Company, and Reynolds American Services Company (Orzechowski and Walker, 2014). Since The Tobacco Institute (an industry-funded group) published the report from 1982 through 1998, it is safe to assume that all the reports, including the one used by Stehr (2005) (not available online), were funded by the industry. While it is not ideal to use industry (or industry-sponsored) data for tax-paid consumption, this is often the only data available.

Stehr (2005) reported results for the gap analysis by looking at per capita daily cigarette consumption, instead of aggregate consumption. A similar approach was used by Blecher (2010), who reported results as cigarettes per smoker per year. Another approach is to report consumption at the aggregate level (i.e. what all smokers in a country consume), as was done by Paraje (2018) and Guindon, Burkhalter & Brown (2017).

Stehr (2005) found that, at a national level, tax-paid sales decreased faster than the decrease in self-reported consumption over the period 1985–2001, indicating an increase in illicit trade. The author assumed constant levels of under-reporting, but made no assumptions about the actual level of under-reporting.

Vietnam

Nguyen et al. (2014) measured illicit cigarette trade in Vietnam from 1998 to 2010 using two methods: gap analysis and trade discrepancies recorded by Vietnam and trade partners.

For the gap analysis, tobacco consumption was estimated for four years for which data were available: the Vietnam Living Standards Survey 1998, the Vietnam National Health Survey 2002, the Vietnam Household Living Standards Survey 2006, and the Global Adult Tobacco Survey Vietnam 2010. Tax-paid sales were provided by the Ministry of Industry and Trade, who received data from the Vietnam Tobacco Association. Annual national cigarette consumption is the product of the average number of cigarettes smoked each day per smoker by gender and age group, the numbers of smokers in each group, and the number of days in a year.

Nguyen et al. (2014) presented results in two ways: (1) the ratio of consumption as a proportion of legal sales, and (2) illicit consumption as a share of the total consumption. Both approaches employed three levels of under-reporting (10%, 20%, and 30%). When 10% under-reporting was applied to the survey data, illicit cigarette consumption was estimated to represent 0.7% of total consumption in 1998, 5.9% in 2002, 1.5% in 2006, and -46.1% in 2010.

The authors explain the strange negative result for 2010 as an apparent and growing surplus of cigarettes in the Vietnamese market, which suggests that it is possible that the estimates of consumption, legal sales, or both, were inaccurate for 2010. From 2006 to 2010, legal sales rose by more than 40%, yet the Vietnamese population increased by only 4%, and aggregate consumption, based on survey data, decreased.

Chile (paper not in English)

According to Paraje (2018), Debrott Sanchez (2006), who looked at the Chilean population, compared consumption reported in a 2002 survey with domestic sales (provided by the tobacco industry). Debrott Sanchez (2006) concluded that illicit trade that year was 4.2% of the local market. Paraje (2018) noted that Debrott Sanchez (2006) did not consider under-reporting of cigarette smoking. Paraje (2018) also noted that the estimates may be unreliable as the author used just one survey and failed to consider another point in time. This is particularly problematic if under-reporting is high.

Under-reporting estimates from the various studies

The assumptions regarding the level of under-reporting of survey consumption varies widely across studies (Table 4.2). Although not explicitly stated, existing research seems to adjust for under-reporting by increasing self-reported consumption by $x*(1+y)$, where x is self-reported cigarette consumption and y is the under-reporting percentage. For example, if under-reporting is estimated at 20%, and self-reported cigarette consumption is equal to 80 cigarettes, then true consumption is estimated to equal 96 cigarettes (80*(1+0.2)). For 20% under-reporting I use the formula $x/(1-y)$. If a smoker reports smoking 80 cigarettes, but his/her actual consumption is 100, true consumption (100 cigarettes) is under-reported by 20%: 80/(1−0.2)=100. The second calculation, used in this paper, is more accurate. For small under-reporting estimates, the method of calculation does not result is significant differences, but for large estimates of under-reporting, the difference in true consumption using the two different formulas is substantial.

Table 4.2: Under-reporting assumptions across studies

Country (Author, year)	**Levels of under-reporting**
South Africa (Blecher, 2010)	5 and 10%.
Argentina, Brazil, Chile, Colombia and Peru (Paraje, 2018)	No assumptions about the level of under-reporting, but assumed that under-reporting was consistent over time.
Brazil (Szklo et al., 2018)	The authors estimated that under-reporting is 88% among individuals with lower levels of education and 82% for individuals with higher levels of education.
Canada (Guindon, Burkhalter & Brown, 2017)	Aside from trends, the authors also presented estimates for illicit trade in Ontario using under-reporting levels of 35% and 40%.
United Kingdom (Her Majesty's Revenue and Customs, 5 March 2020)	Although the exact value of the uplift factor was not specified in the reports, correspondence with HMRC revealed an uplift factor of 1.46 applied to cigarettes (i.e. 31.5%).
United States (Stehr, 2005)	No assumptions about the level of under-reporting, but assumed that under-reporting is consistent over time.
Vietnam (Nguyen et al., 2014)	10%, 20%, and 30%.
Chile (Debrott Sánchez, 2006)	Did not account for under-reporting.

METHODS AND DATA

Gap analysis

Gap analysis has been explained in several toolkits including Merriman (2002) and Ross (2015). Gap analysis is based on the premise that total cigarette consumption in a country is equal to legal (tax-paid) consumption of cigarettes plus illicit consumption (Merriman, 2002).

The total market for cigarettes is defined as:

$$Q = Q_L + Q_I \ldots\ldots\ldots\ldots\ldots(1)$$

Where Q is the total quantity of cigarettes consumed, Q_L is the quantity of legal cigarettes consumed, and Q_I is the quantity of illicit cigarettes consumed (Blecher, 2010). The number of people who smoke, i.e., the smoking population (P_S), is calculated by multiplying the population (P) by smoking prevalence (R):

$$P_S = P \times R \ldots\ldots\ldots\ldots\ldots(2)$$

The size of the total market (Q) is calculated by multiplying the smoking population (P_S) by the average consumption per smoker or smoking intensity (A):

$$Q = P_S \times A \ldots\ldots\ldots\ldots\ldots(3)$$

The quantity of illicit cigarettes consumed (Q_I) is calculated by substituting equation 3 into equation 1:

$$Q_I = (P_S \times A) - Q_L$$

Therefore, the size of the illicit market (Q_I) can be calculated if data are available for the legal market (Q_L), the smoking population (P_S), and smoking intensity (A). Data on the legal market (Q_L), which includes domestic production and imported cigarettes, are obtained from official statistics. Smoking population (P_S) and smoking intensity (A) are obtained from survey data. Total consumption in a given period is estimated by multiplying the smoking population (P_S) and the smoking intensity (A).

Self-reported consumption: Data from two national surveys

I used data from two nationally representative surveys to estimate the total size of the South African cigarette market: the All Media and Products Survey (AMPS) (2002 – 2015) (South African Audience Research Foundation, 2002; South African Audience Research Foundation, 2014) and the National Income Dynamics Study (NIDS) (2008, 2010, 2012, 2015, 2017) (Southern Africa Labour and Development Research Unit).

1. All Media and Products Survey (AMPS)

AMPS, a cross-sectional survey, considered the use of products (e.g. cigarettes, alcohol, and energy drinks), traditional media (e.g. newspapers), and services (e.g. banking). It was conducted annually since 1993, but was discontinued in 2015. It used a multi-stage, area-stratified probability sample and provided sample weights to represent the South Africa population (South Africa Market Audience Foundation).

For the 2002 survey, information on cigarettes was grouped with other items. Respondents were asked: ‘Please indicate for each of the following items, on average, the **NUMBER** that you **PERSONALLY SMOKE, DRINK OR USE PER DAY**’. The question was simplified in the 2003 to 2011 surveys to: ‘How many **cigarettes** did you personally smoke **YESTERDAY**?’ From 2010 to 2015 respondents were asked: ‘Please indicate which **ONE** of the following statements applies to you: (1) I have never smoked, (2) I used to smoke but I stopped smoking”, (3) I stopped smoking, but have started again, (4) I smoke, but intend stopping in the near future, or (5) I smoke and have no intention of quitting’. From 2002 to 2008, AMPS included respondents aged 16 years and older, while 15-year-olds were added in subsequent years.

From 2012 to 2015, respondents were not asked about the number of cigarettes smoked, which is an important variable for the gap analysis. The estimates from 2012 onwards were based on two assumptions. First, to calculate the annual self-reported consumption, I assumed that the average daily number of cigarettes smoked from 2012 to 2015 remained at the AMPS 2011 level of 9.1 cigarettes per smoker, based on the fact that NIDS indicated that the number of cigarettes smoked per smoker between 2012 and 2015 remained statistically the same. According to NIDS, smoking intensity in 2012 was 8.28 cigarettes per day (95% CI: 8.05–8.50), which decreased marginally and not significantly to 8.25 cigarettes per day in 2015 (95% CI: 8.03–8.47). In addition, there were no major legislative or tax-related changes post-2011, so the assumption that the average daily number of cigarettes consumed by smokers was unlikely to have changed much seems reasonable.

Secondly, for 2016 and 2017, where AMPS data does not exist, I assumed that the total number of cigarettes consumed annually remained at the 2015 level. While this assumption may seem somewhat heroic at the outset, I believe that it is not unrealistic. As with the assumption for smoking intensity, there were no significant tobacco control interventions between 2015 and 2017. Furthermore, NIDS data for 2015 – 2017 followed a similar trend.

2. *National Income Dynamics Survey (NIDS)*

There are five smoking-related questions in the NIDS adult questionnaire, which are consistent over all waves: (1) ‘Do you smoke cigarettes?’, (2) ‘Did you ever smoke cigarettes regularly?’, (3) ‘How old were you when you last smoked cigarettes regularly?’, (4) ‘How old were you when you first smoked cigarettes regularly?’, and (5) ‘On average, how many cigarettes per day did you/do you smoke?'. The adult questionnaires were completed by respondents aged 15 years and older. Questions (1) and (5) were used in the analysis.

Weights (created by the NIDS team) were applied to scale up the estimates to represent the population. A two-stage procedure was used to calculate weights: (1) design weights were calculated as the inverse of the probability of inclusion, and (2) weights were adjusted such that the age, sex, and race totals of the NIDS data matched the mid-year population estimates produced by Stats SA. To correct for attrition between waves, new sample members were included in waves subsequent to the first wave of 2008. Although NIDS is a panel survey, I treated each dataset as a cross-section.

Accounting for under-reporting in survey data

Under-reported cigarette consumption in survey data is one of the weaknesses of the gap analysis method. It is widely accepted that people under-report cigarette consumption (Dietz et al., 2011; International Agency for Research on Cancer, 2011; Pérez-Stable et al., 1990; Roth et al., 2009; Warner, 1978). Under-reporting occurs both at the prevalence level (people do not admit to being smokers), and at the smoking intensity level (people under-report the number of cigarettes smoked).

For the three years for which AMPS and NIDS data overlap (2008, 2010, and 2012), the average difference in prevalence estimates is 2 percentage points (AMPS is higher than NIDS). Differences in prevalence estimates from different surveys are not uncommon: a 2017 paper comparing smoking prevalence estimates from two Canadian national surveys found an average difference of 3.5 percentage points for the years 2001 to 2013 (Gagné, 2017).

The variance in prevalence estimates could reflect differences in the way the cigarette consumption questions are worded, different sample methodologies, and different questionnaire content. AMPS, a product-use survey, asked about specific brands used (such as groceries, cleaning products, cosmetics, medication, and alcohol), while NIDS asked about income, consumption, expenditure, fertility, mortality, health, education, and expectations about the future. It seems likely that respondents to the AMPS questionnaire might have answered more honestly than respondents to the NIDS questionnaire, given that AMPS focused purely on consumption. Prior to the smoking-behaviour questions, NIDS respondents were asked health-related questions, which might have primed respondents to be less truthful about their smoking habits. This may have resulted in less under-reporting in AMPS than in NIDS.

Smoking intensity may also be under-reported because of recall error, where participants do not correctly remember how many cigarettes they consumed (Ross, 2015). Survey respondents also tend to report their consumption in round numbers, e.g. at 5, 10 and 20 cigarettes per day.

To account for under-reporting, annual self-reported consumption were inflated. Under-reporting estimates of 5% and 10% were used for AMPS, while for NIDS, 15% and 20% were used. The calculation for 5% under-reporting is x/0.95, where x is self-reported consumption. These percentages ensured that the volume of illicit trade was not less than zero, since the concept of negative illicit trade is nonsensical. For example, if under-reporting is not accounted for in NIDS 2010, illicit trade is estimated to be −7.4% ((21.93−23.56)/21.93). Tax-paid consumption is estimated at 23.56 billion cigarettes in 2010, while self-reported consumption according to NIDS 2010 is 21.93 billion cigarettes. Self-reported consumption should be equal to or greater than tax-paid consumption.

Confidence intervals for self-reported cigarette consumption

To create confidence intervals around annual self-reported cigarette consumption, Stata version 16.0 was used to bootstrap the point estimate of the product of smoking status and smoking intensity. Bootstrapping obtains a valid standard error by computing the estimate from different random samples drawn from the original data (Wooldridge, 2013). The bootstrap method to calculate confidence intervals around self-reported cigarette consumption was used by Paraje (2018).

Smoking status is a discrete variable (1: smoker, 0: non-smoker), while cigarette consumption is a continuous variable. Respondents who reported that they smoked, but did not report the number of cigarettes they smoked per day, were assigned the mean value of smoking intensity in that year. For example, in NIDS 2017, 173 smokers (4.4% of all smokers) were assigned a smoking intensity value of 8.04 cigarettes. Where I did not have smoking intensity data (AMPS 2012 − 2015), I only bootstrapped the number of smokers, assuming smoking intensity of 9.1 cigarette per day for each smoker.

Since the bootstrap command does not allow for weights to be accounted for using the `svy` command, I multiplied smoking*intensity by the weight variable before bootstrapping. All missing values were dropped before running the bootstrap command (failing to do so resulted in error messages). I specified 1000 repetitions in the bootstrap command, which was sufficient to obtain valid estimates, but not too onerous computationally. A seed number was also specified so that the results remained the same when the command was rerun.

Once the point estimate was obtained, it was multiplied by 365, and the total number of respondents in each respective survey. For example, in NIDS 2015, annual self-reported consumption was 23.49 billion cigarettes (2865 cigarettes per day (bootstrap point estimate) * 365(days per year) * 22 493 (number of respondents)). To obtain the 99% confidence intervals for annual self-reporting cigarette consumption, the same formula was applied, using the lower and upper bound estimates. While 95% confidence intervals would have been sufficient, 99% was chosen to make inferences more robust.

An alternative method to calculate annual self-reported cigarette consumption confidence intervals is discussed in the sensitivity analysis. This method was used by Guindon, Burkhalter & Brown (2017), although using different software (SAS).

United Nations (UN) population data

In order to standardise population estimates across the two surveys and to smooth the data, I used population estimates from the United Nations (age 15+). Since both AMPS and NIDS surveys consistently report lower population estimates than the UN data, I used an uplift factor to inflate the weights. For AMPS the uplift factor from 2002 to 2015 averaged 1.09 (standard deviation = 0.04, minimum = 1.03, maximum = 1.15), while for NIDS it averaged 1.17 (standard deviation = 0.04, minimum = 1.15, maximum = 1.24).

Tax-paid consumption data: National Treasury & Department of Trade & Industry

The amount of excise revenue received from domestic cigarettes was obtained from annual national budgets compiled by the National Treasury of South Africa (Republic of South Africa: National Treasury). Excise tax revenue captured as ‘Cigarettes and cigarette tobacco’ essentially represents excise tax collections from ‘cigarettes’, since the market share of ‘cigarette tobacco’ is marginal. While it would have be useful to analyse illicit trade at a provincial level in South Africa, this was not possible as excise tax from cigarettes is reported at a national level.

For each financial year (from April to March of the following year), I obtained the number of cigarettes sold by dividing the excise revenue by the excise tax per cigarette, which is levied as a specific tax in South Africa. For example, in the fiscal year 2014/2015, Treasury collected R12 602 million rand from cigarette excise taxes and the excise tax was R11.60 per pack of 20 cigarettes. The total number of packs on which excise tax was paid in 2014/2015 is 1 086 million (R12 602/11.6). To convert packs to cigarettes, the number of packs was multiplied by 20. The data were then converted to the calendar year by using appropriate weightings, i.e. the last three months of one financial year (January to March) and the first nine months of the following financial year (April to December).

Excise tax received from imported cigarettes is captured as part of 'Miscellaneous customs and excise receipts'. Since the category includes other products, it was not possible to establish the amount received from cigarettes. Instead, kilograms of imported cigarettes were obtained from the Department of Trade and Industry's website (Republic of South Africa: Department of Trade and Industry, 2019). The declared mass of cigarettes was converted to number of cigarettes using a conversion rate of 1 kg = 1000 cigarettes (Organisation for Economic Co-operation and Development, 2018).

Since there is substantial variation in the data (in particular, there are three spikes in the data, one of which does not correspond with an increase in revenue received), the median number of imports from 2002 to 2015 (1.9 billion cigarettes a year) was used. The numbers for 2016 (3.0 billion) and 2017 (3.4 billion) were left unchanged, as, according to SARS, cigarette imports increased significantly in these two years.

2016 South African Demographic and Health Survey (DHS)

One way to test whether NIDS data captured occasional smokers is to compare data from NIDS to the Demographic and Health Survey (DHS). DHS asked respondents about daily and occasional smoking, whereas NIDS asked respondents whether or not they smoked cigarettes. It is hypothesised that if the sum of daily and occasional smoking from DHS is close to NIDS current smoking prevalence, then NIDS captured occasional smokers. If NIDS smoking prevalence is substantially lower than the sum of daily and occasional smokers in DHS, then this would indicate that the wording of the smoking behaviour question in the NIDS survey is problematic, which could result in under-reporting in self-reported cigarette consumption.

Results were computed using Stata version 16.0 and Microsoft Excel.

RESULTS

Table 4.3 presents summary statistics from AMPS, NIDS, the United Nations, National Treasury, and the Department of Trade and Industry. Column 3 shows the total South African population retrieved from the United Nations database (age 15+) (United Nations Department of Economic and Social Affairs. Population Division). Between 2002 and 2010, smoking prevalence, as reported in AMPS, decreased from 25.2% (99% CI: 24.5–25.8) to 19.8% (99% CI: 19.1–20.4), followed by an increase to 21.7% (99% CI: 21.0–22.4) in 2015 (Column 4). Smoking prevalence, as reported in NIDS, decreased between 2008 and 2010, and then increased in 2012 and 2015, followed by a slight decrease in 2017. Overall, smoking prevalence based on

NIDS data decreased slightly from 21.1% (99% CI: 20.3–22.0) in 2008 to 19.9% (99% CI: 19.2–20.6) in 2017.

Smoking intensity (i.e. the average number of cigarettes smoked per smoker per day) is shown in Column 6. AMPS indicates a slight decrease in smoking intensity between 2003 and 2008, followed by a slight upward trend. Based on AMPS data, smoking intensity averaged 8.9 cigarettes a day in the 2002 − 2011 period (standard deviation = 0.2, minimum = 8.7, maximum = 9.2), while it averaged 8.4 cigarettes a day in the 2008 − 2017 NIDS surveys (standard deviation = 0.3, minimum = 8.0, maximum = 8.8). The average number of cigarettes smoked per day remained fairly constant between 2002 and 2011 (mean = 8.9), While AMPS reported higher levels of consumption than NIDS, both surveys reported similar trends (Column 7). For example, between 2008 and 2010, AMPS reported a decrease of 7.8% in consumption while NIDS reported an 8.9% decrease.

Table 4.3: Summary Statistics

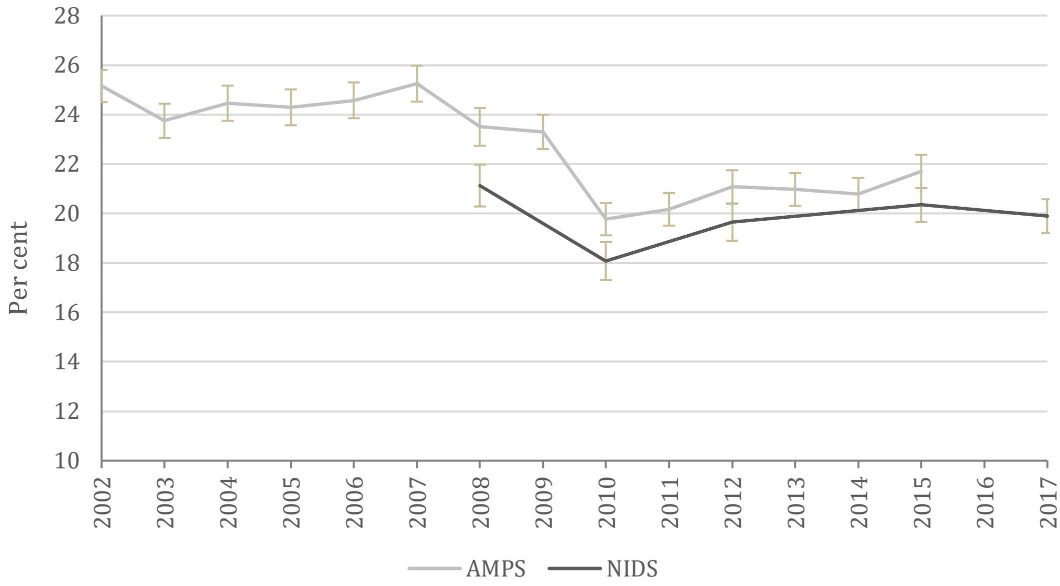
Survey (1)	Year (2)	Total adult population (million) (3)	Smoking prevalence (%) (4)	Number of smokers (million) (5)	Average daily intensity (6)	Annual self-reported consumption (billion) (7)	Tax-paid consumption (National Treasury and Department of Trade & Industry) (billion) (8)
AMPS	2002	31.6	25.2 (24.5; 25.8)	7.9 (7.7; 8.2)	9.1 (8.9; 9.3)	26.3 (25.3; 27.4)	26.1
	2003	32.2	23.7 (23.1; 24.4)	7.6 (7.4; 7.9)	9.2 (8.9; 9.4)	25.6 (24.5; 26.6)	26.0
	2004	32.8	24.5 (23.7; 25.2)	8.0 (7.8; 8.3)	8.9 (8.7; 9.1)	26.0 (24.9; 27.1)	25.6
	2005	33.4	24.3 (23.6; 25.0)	8.1 (7.9; 8.4)	8.8 (8.6; 9.0)	26.1 (24.9; 27.3)	25.7
	2006	33.9	24.6 (23.9; 25.3)	8.3 (8.1; 8.6)	8.7 (8.5; 8.9)	26.5 (25.3; 27.7)	26.2
	2007	34.4	25.3 (24.5; 26.0)	8.68 (8.4; 8.9)	8.7 (8.5; 8.9)	27.6 (26.3; 28.9)	26.7
	2008	34.9	23.5 (22.7; 24.3)	8.2 (7.9; 8.5)	8.7 (8.4; 8.9)	25.9 (24.4; 27.3)	27.2
	2009	35.4	23.3 (22.6; 24.0)	8.2 (8.0; 8.5)	8.8 (8.6; 9.0)	26.4 (25.0; 27.7)	26.1
	2010	35.9	19.8 (19.1; 20.4)	7.1 (6.9; 7.3)	9.2 (9.0; 9.5)	23.9 (22.7; 25.1)	23.6
	2011	36.5	20.2 (19.5; 20.8)	7.4 (7.1; 7.6)	9.1 (8.9; 9.3)	24.4 (23.1; 25.7)	22.8
	2012	37.1	21.1 (20.4; 21.8)	7.8 (7.6; 8.1)	*9.1*	*26.0* *(24.8; 27.2)*	23.1
	2013	37.8	21.0 (20.3; 21.6)	7.9 (7.7; 8.2)	*9.1*	*26.3* *(25.1; 27.5)*	22.2
	2014	38.4	20.8 (20.1; 21.4)	8.0 (7.7; 8.2)	*9.1*	*26.51* *(25.29; 27.7)*	23.2
	2015	39.1	21.7 (21.0; 22.4)	8.5 (8.2; 8.7)	*9.1*	*28.2* *(26.9; 29.4)*	23.0
	2016	39.7				*28.2*	22.0
	2017	40.3				*28.2*	19.4
NIDS	2008	34.9	21.1 (20.3; 22.0)	7.4 (7.1; 7.7)	8.5 (8.2; 8.8)	22.9 (20.8; 25.0)	27.2
	2010	35.9	18.1 (17.3; 18.8)	6.5 (6.2; 6.8)	8.8 (8.4; 9.2)	20.9 (17.5; 24.2)	23.6
	2012	37.1	19.7 (18.9; 20.4)	7.3 (7.0; 7.6)	8.3 (8.0; 8.6)	22.0 (19.3; 24.8)	23.1
	2015	39.1	20.3 (19.7; 21.0)	8.0 (7.7; 8.2)	8.3 (8.0; 8.5)	23.9 (21.0; 26.8)	23.0
	2017	40.3	19.9 (19.2; 20.6)	8.0 (7.7; 8.3)	8.0 (7.8; 8.3)	23.5 (20.4; 26.6)	19.4

Source: All Media Products Survey (AMPS) 2002 – 2015, National Income Dynamics Study (NIDS), 2008, 2010, 2012, 2015, and 2017, United Nations, National Treasury, and the Department of Trade and Industry.

Notes: AMPS samples sizes vary between 20 377 to 29 458 respondents. NIDS sample sizes vary between 15 556 and 22 493 respondents. Numbers in brackets show 99% confidence intervals. Numbers in italics (AMPS data, column 7) are the author's own estimates: (1) smoking intensity in 2012 to 2015 were assumed to remain at the 2011 estimate of 9.1 cigarettes per day, and (2) annual self-reported consumption from 2016 to 2017 remained at the 2015 level of 28.15 billion cigarettes.

Smoking prevalence reported by NIDS is consistently and significantly lower than AMPS estimates for overlapping years (Figure 4.1). However, the trends produced by both surveys are consistent over time.

Figure 4.1: Smoking prevalence: AMPS (2002 – 2015) and NIDS (2008 – 2017)



Notes: Error bars indicate 99% confidence intervals.

Occasional smokers

Occasional smokers are described using a number of different terms including 'non-daily smokers', 'intermittent smokers', and 'social smokers' (Edwards et al., 2010). A 2010 paper that investigates occasional smokers in Canada finds that, relative to daily smokers, occasional smokers tend to be younger, more educated, and less likely to report smoking in the home and workplace environments (Edwards et al., 2010).

If occasional smokers did not report their consumption in NIDS and AMPS, estimates of self-reported consumption will be artificially lower than true consumption. If self-reported consumption is in fact higher than what is captured by the data, then illicit trade will be higher than the estimated size of the illicit market, as the gap between self-reported consumption and government data would then be wider.

The cigarette consumption question in the AMPS survey is: 'How many cigarettes did you smoke yesterday?' Respondents who smoke less than daily, but smoked the previous day, would be considered smokers, and their consumption would be included in the analysis. On the other hand, respondents who smoke less than daily, and who did not smoke the previous day, would not be considered smokers, and their consumption would not be included in the analysis. The latter group may result in significant under-reporting, which would affect the estimate of the size of the illicit market.

In NIDS, smokers and ex-smokers were asked: 'On average, how many cigarettes per day did you/do you smoke?' Respondents who smoke one cigarette four times a week should answer 'one' to this question. However, some of these respondents might not consider themselves smokers. They may have answered 'no' to the question 'Do you smoke cigarettes?' In these cases, respondents would not have been asked the smoking intensity question, as it was only asked to current and ex-smokers.

To estimate occasional smoking prevalence, I used the 2016 South African DHS (Demographic and Health Survey, 2016), which asked about both daily and occasional (weekly and less than weekly) smoking. Table 4.4 shows smoking prevalence estimates from DHS 2016 and NIDS 2017 for a comparable age group (ages 15 – 49). Despite the different year and differently-worded questions, comparisons are possible.

Table 4.4: Prevalence estimates from DHS 2016 and NIDS 2017 (weighted data; ages 15−49; 99% CI in brackets)

	DHS 2016		**NIDS 2017**	
	Male	Female	Male	Female
Daily smoker	27.6% (25.8−29.4)	5.2% (4.5−6.0)	Unknown	Unknown
Occasional smoker (weekly and less than weekly)	6.4% (5.4−7.3)	1.1% (0.8−1.4)	Unknown	Unknown
Current smoker	33.9%* (32.1−35.8)	6.3%* (5.5−7.1)	33.9% (32.4−35.3)	7.5% (6.8−8.2)

Notes: *daily or occasional smoking prevalence

According the DHS 2016, daily smoking prevalence among males was 27.6% and occasional smoking prevalence 6.4%, a total of 33.9% (99% CI: 32.1−35.8). NIDS reports the same smoking prevalence of 33.9% but with a slightly narrower confidence interval (99% CI: (32.4–35.3). For females, DHS 2016 reported daily smoking at 5.2% and occasional smoking at 1.1%, a total of 6.3% (99% CI: 5.5–7.1), which is slightly lower than the current smoking prevalence of 7.5% (99% CI: (6.8–8.2) reported in NIDS 2017. The results indicate that most occasional smokers are captured in the NIDS smoking prevalence estimates.

Tax-paid consumption and survey-based consumption

The gap method of estimating the size of the illicit market focuses on the difference between tax-paid consumption and survey-based consumption. Tax-paid consumption (as recorded by the National Treasury and the Department of Trade and Industry) and survey-based consumption, as recorded by AMPS (Figure 4.2) and NIDS (Figure 4.3), was set equal to 100 in the initial year (2002 for AMPS and 2008 for NIDS). Comparing trends in these two measures of consumption provides information on changes in illicit trade over time, and does not require any assumptions about the level of under-reporting in survey data.

Between 2002 and 2009, illicit trade remained at levels close to that of the base year. Levels of illicit trade began to change from 2009, when registered sales were slightly lower than self-reported consumption. Both Figures 4.2 (AMPS data) and 4.3 (NIDS data) show that from 2010 tax-paid consumption declined steeply, indicating an increase in illicit trade, which became statistically significant from 2011.

Figure 4.2: Annual survey-based consumption (AMPS) and tax-paid consumption: 2002−2015 (2002=100)

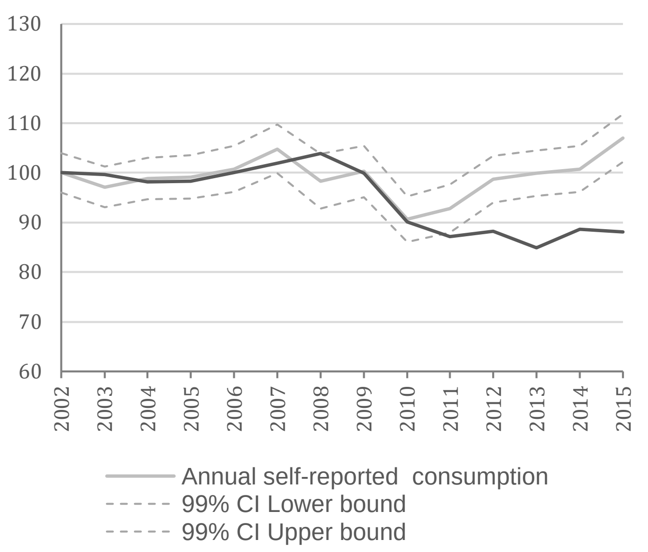
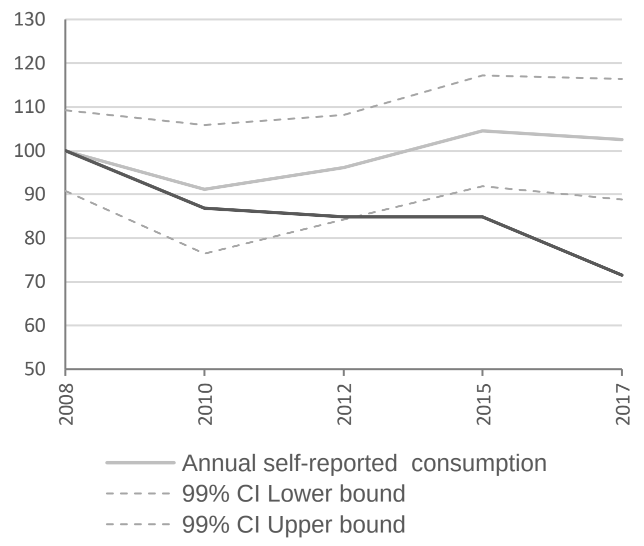


Figure 4.3: Annual survey-based consumption (NIDS) and tax-paid consumption: 2008−2017 (2008=100)



Ratio of tax-paid consumption to survey-based consumption

Figures 4.4 to 4.7 present the ratio of self-reported cigarette consumption (from AMPS and NIDS) to tax-paid consumption. A rising index indicates either an increasing share of illicit cigarette sales or a decrease in the under-reporting of self-reported cigarette consumption (Guindon, Burkhalter & Brown, 2017). In South Africa, it seems unlikely that under-reporting has changed over the period of interest as there have been no significant policy changes that would have resulted in an increase in under-reporting. Therefore, the increase is likely to be the result of an increase in illicit trade. Figures 4.6 and 4.7 show the same index, but over a comparable time period: 2008 to 2015 (base 2008).

Figure 4.4: Ratio of self-reported cigarette consumption to tax-paid consumption: AMPS 2002 – 2015 (2002=100)

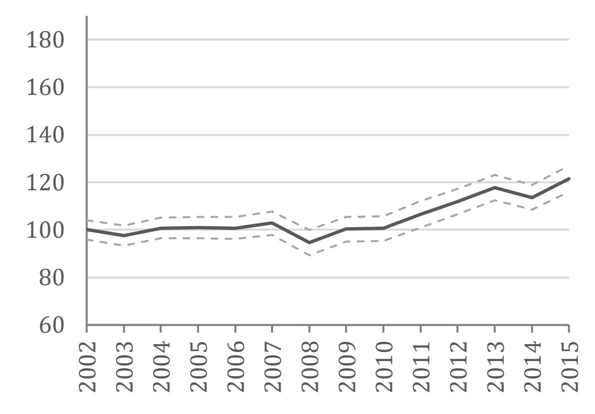


Figure 4.5: Ratio of self-reported cigarette consumption to tax-paid consumption: NIDS 2008 – 2017 (2008=100)

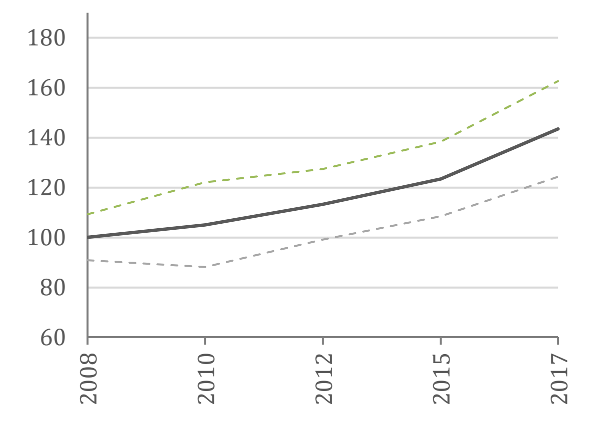


Figure 4.6: Ratio of self-reported cigarette consumption to tax-paid consumption: AMPS 2008 – 2015 (2008=100)

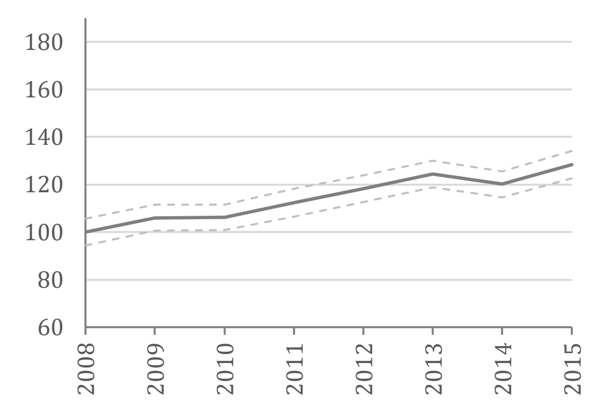
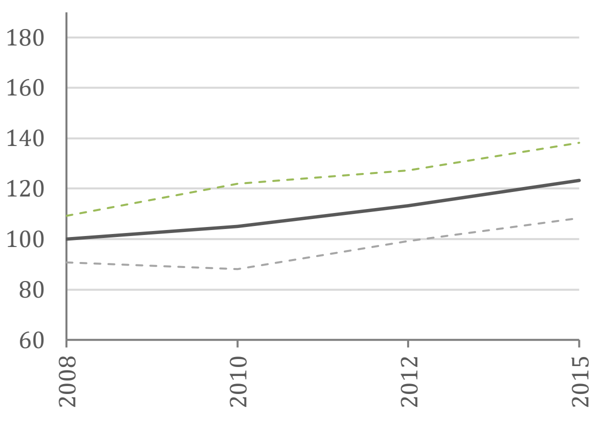


Figure 4.7: Ratio of self-reported cigarette consumption to tax-paid consumption: NIDS 2008 – 2015 (2008=100)

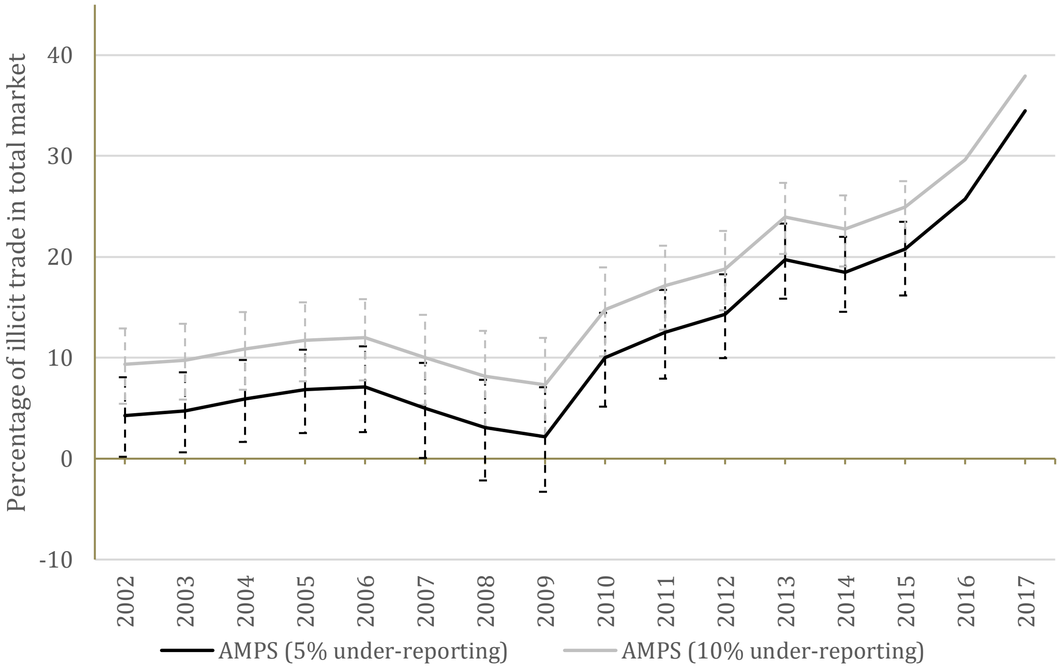


Source: Self-reported annual consumption from All Media Products Survey (Figures 4.4 and 4.6) and National Income Dynamics Study (Figures 4.5 and 4.7); tax-based consumption from National Treasury and Department of Trade and Industry. Notes: Dashed lines represent 99% CIs. The confidence intervals are wider in NIDS because the samples are smaller than AMPS.

Percentage of illicit trade in the total market

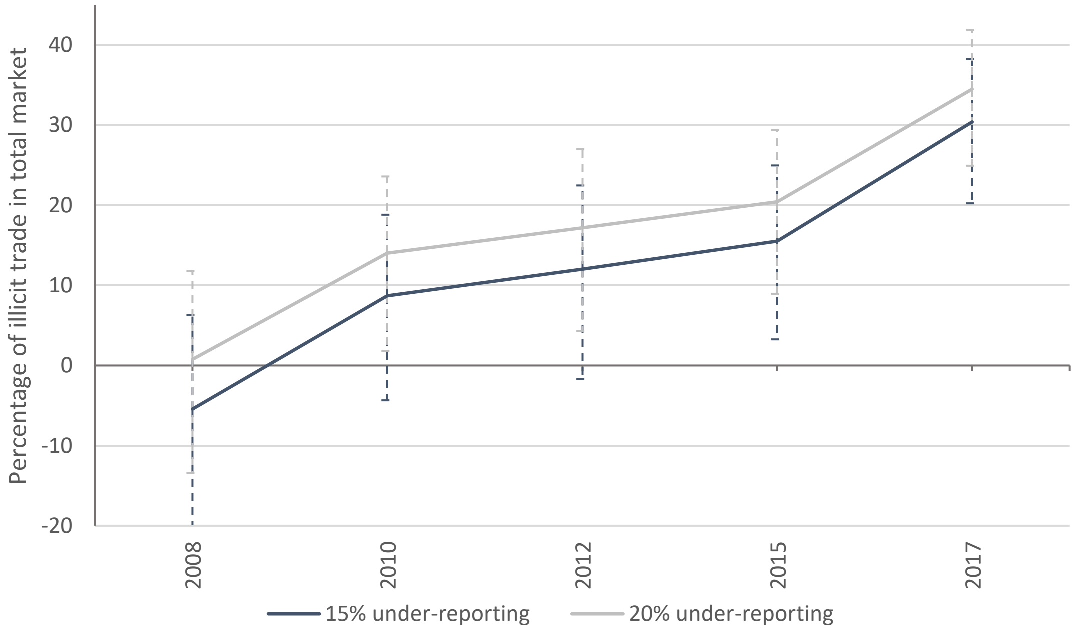
Illicit trade as a share of the total market was calculated as the gap (self-reported consumption less tax-paid consumption) divided by self-reported consumption (Figures 4.8 and 4.9). A three-year centered moving average was applied to self-reported consumption estimates to smooth the data. For the beginning and end years, the average of two years was used, i.e. for AMPS 2002 (2002 and 2003) and 2017 (2016 and 2017), and for NIDS 2008 (2008 and 2010) and 2017 (2015 and 2017). Assuming self-reported cigarette sales were under-reported by 5% in the AMPS data, illicit trade hovered around 5% from 2002 to 2009, followed by a sharp increase: from 2009 to 2017, illicit trade increased from approximately 2% to 35%. The analysis of both AMPS and NIDS datasets shows a steep increase in illicit trade between 2015 and 2017. In 2017, illicit trade using AMPS data was between 35% (5% under-reporting) and 38% (10% under-reporting), which is similar to NIDS: 30% (15% under-reporting) and 35% (20% under-reporting).

Figure 4.8: Share of Illicit Cigarettes in the Total Market in South Africa using AMPS data: 2002 – 2017



Notes: Error bars indicate 99% confidence intervals.

Figure 4.9: Share of Illicit Cigarettes in the Total Market in South Africa using NIDS data: 2008 – 2017



Notes: Error bars indicate 99% confidence intervals.

SENSITIVITY ANALYSIS

Population data from different sources

In the main analysis, the NIDS and AMPS data were weighted to the UN population projections. The effect of different population estimates may widen or narrow the gap between annual self-reported consumption (from survey data) and tax-paid consumption (from government data). Higher population estimates result in a greater number of smokers, and therefore higher estimates of self-reported consumption. The gap between self-reported consumption and tax-paid consumption will be wider, resulting in higher estimates of illicit trade. It is therefore crucial that the most accurate population data were used.

UN population projections were chosen following advice from Professor Tom Moultrie, a professor of Actuarial Sciences at UCT. He suggested using UN data, which coincides with World Bank (WB) estimates. He explained that Stats SA mid-year estimates are hard to work with as Stats SA changes their model and updates it yearly, which creates confusion.

Table 4.5 (column 2) and Figure 4.10 (orange line) show the unsteadiness of Stats SA's mid-year estimates. Stats SA's projected values (Table 4.5 column 1) and Figure 4.10 (blue line) show a similar trend to UN/WB estimates, but the estimates are consistently lower. The Stats SA projected population data were obtained from the Stats SA website (Statistics South Africa, 2017). Unlike the mid-year population estimates that were extracted from each annual report, the projected data are downloadable as an Excel file. The annual report is an official publication, while the Excel file does not appear to be official.

In order to test the sensitivity of the population estimates chosen for the main analysis, I conducted a robustness check by re-calculating illicit trade using the Stats SA projected population figures.

Table 4.5: Population data from different sources

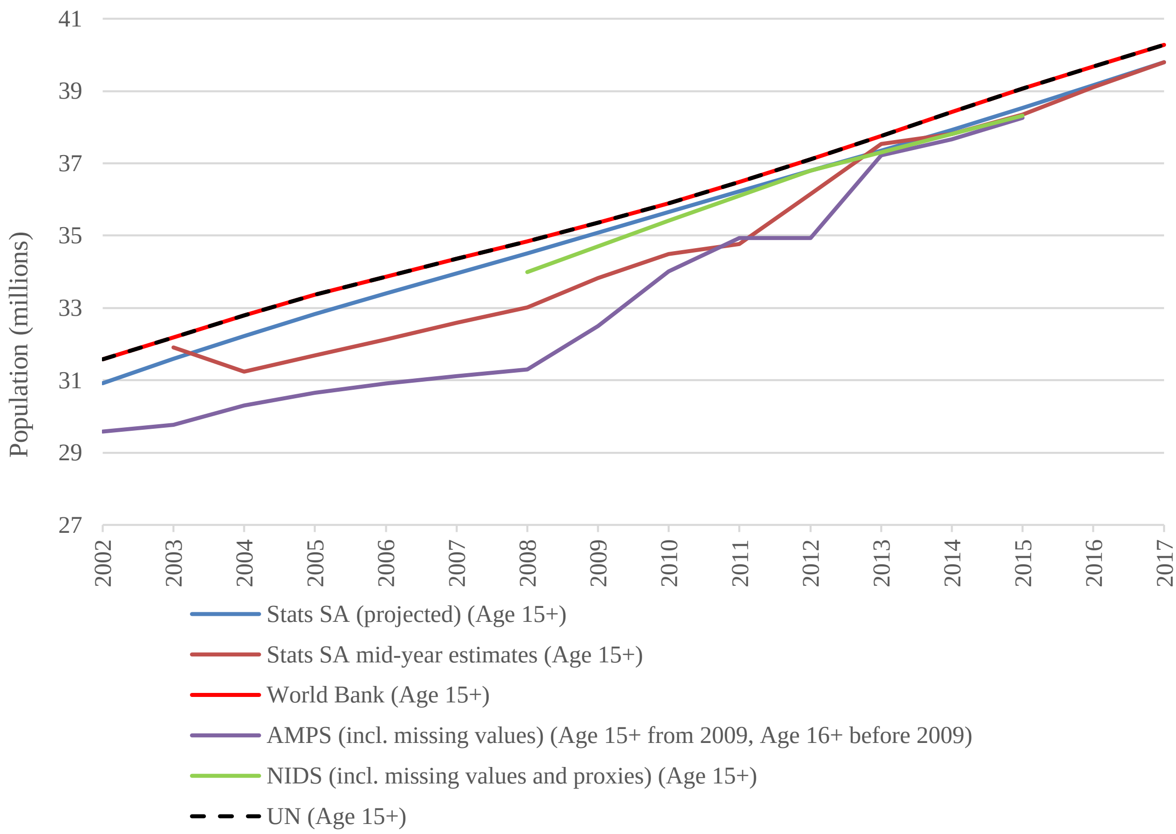
	Stats SA (projected) (Age 15+)*	Stats SA mid-year estimates (Age 15+)**	United Nations (Age 15+)***	World Bank (Age 15+)****	AMPS (including missing values) (Age 15+ from 2009, Age 16+ before 2009)	NIDS (including missing values and proxies) (Age 15+)
	(1)	(2)	(3)	(4)	(5)	(6)
2002	30.9		31.6	31.6	29.6	
2003	31.6	31.9	32.2	32.2	29.8	
2004	32.2	31.2	32.8	32.8	30.3	
2005	32.8	31.7	33.4	33.4	30.7	
2006	33.4	32.1	33.9	33.9	30.9	
2007	34.0	32.6	34.4	34.4	31.1	
2008	34.5	33.0	34.9	34.9	31.3	34.0
2009	35.1	33.8	35.4	35.4	32.5	
2010	35.7	34.5	35.9	35.9	34.0	35.4
2011	36.2	34.8	36.5	36.5	34.9	
2012	36.8	36.2	37.1	37.1	34.9	36.8
2013	37.4	37.5	37.8	37.8	37.2	
2014	37.9	37.8	38.4	38.4	37.7	
2015	38.5	38.3	39.1	39.1	38.3	38.3
2016	39.2	39.1	39.7	39.7		
2017	39.8	39.8	40.3	40.3		

Sources:
*Stats SA. All the data is from a downloaded Excel file titled “Country projections by population group, sex and age (2002-2017)” under a heading “Additional downloads”. http://www.statssa.gov.za/?page_id=1854&PPN=P0302&SCH=7048
**Stats SA. Data is extracted from each yearly report “P0302 – Mid-year population estimates”. http://www.statssa.gov.za/?page_id=1854&PPN=P0302&SCH=7048.
***UN. These are the population estimates used in the main analysis (Table 4.3, column 3) https://population.un.org/wpp/DVD/Files/1_Indicators%20(Standard)/EXCEL_FILES/1_Population/WPP2017_POP_F15_1_ANNUAL_POPULATION_BY_AGE_BOTH_SEXES.xlsx
****World Bank. https://data.worldbank.org/country

NIDS weighted population estimates are close to Stats SA projected estimates. This is unsurprising, since NIDS calculates weights using Stats SA data. On the other hand, AMPS population data estimates prior to 2013 are not close to Stats SA estimates. Some of the difference for the period 2002 to 2008 is explained by the age range sampled over this period: those aged 15 and younger were excluded. From 2009, 15 year olds were included. Prior to 2013, AMPS used population figures from secondary sources. Technical documents for AMPS 2011

(South Africa Market Audience Foundation, 2011) states that population figures for AMPS 2011 were supplied by IHS Global Insight, who took into account mid-year 2011 estimates from Stats SA. This technical document notes that the 2011 methodology is different from the previous Bureau of Market Research model (2010 and earlier) in a number of technical areas. Three of the AMPS datasets (2013 – 2015) coincide almost perfectly with Stats SA estimates.

Figure 4.10: Population data from different sources

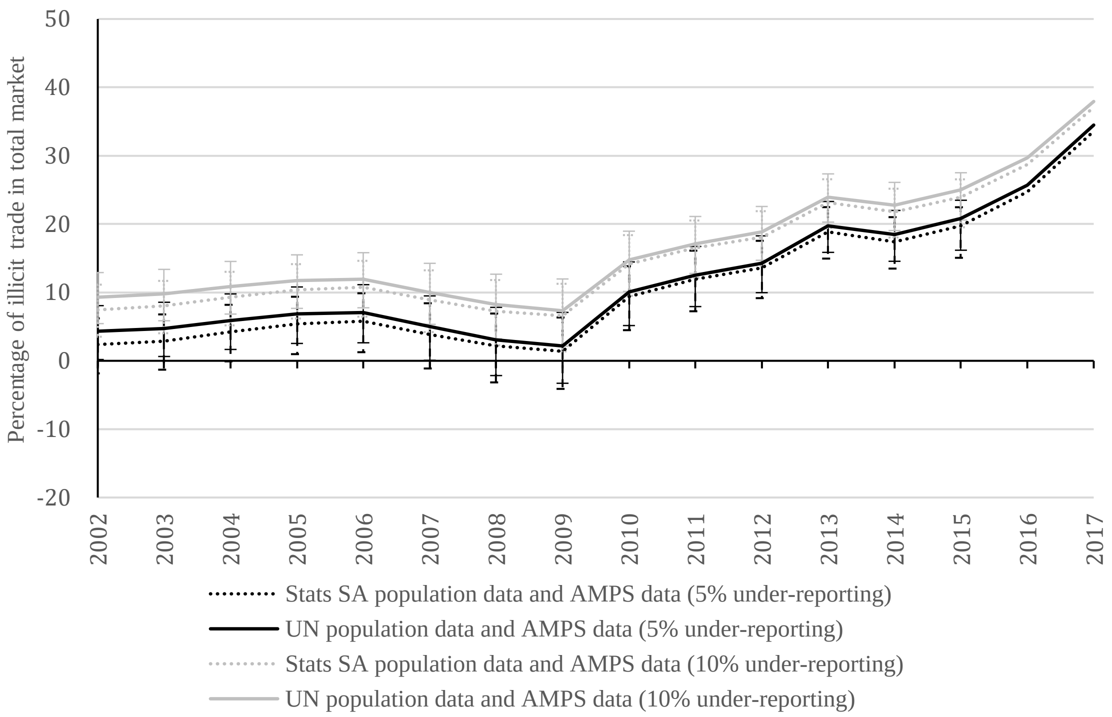


Since Stats SA population estimates are consistently lower than UN/WB estimates, the number of smokers is lower. Self-reported consumption is therefore also lower. The gap between self-reported consumption and tax-paid consumption is then narrower, resulting in lower estimates of illicit trade (Table 4.6 and Figures 4.11 and 4.12). For the 2002 – 2017 period, which is based on the AMPS data, the average difference in illicit trade estimates is 1.13 percentage points (5% under-reporting) and 1.07 percentage points (10% under-reporting). For the five NIDS datasets, the average difference is 0.87 percentage points (5% under-reporting) and 0.82 percentage points (10% under-reporting).

Table 4.6: Illicit trade estimates (%) using population data from Stats SA and UN: AMPS and NIDS

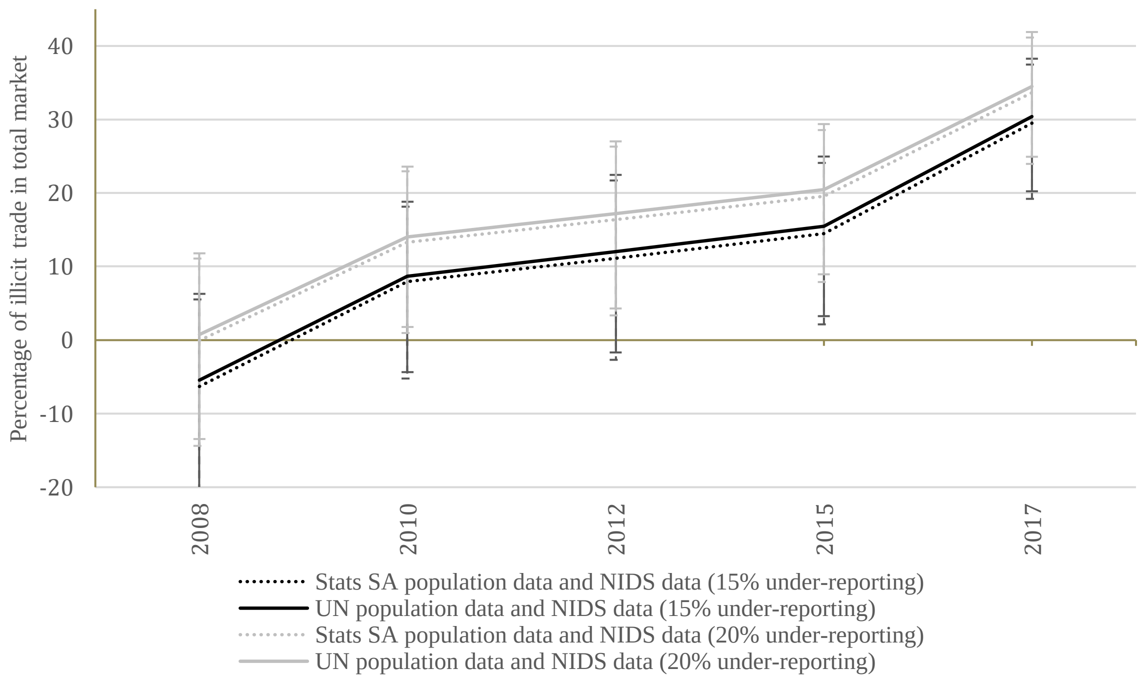
	Stats SA population data	UN population data	Difference in percentage points	Stats SA population data	UN population data	Difference in percentage points
AMPS	5% under-reporting			10% under-reporting		
2002	2.3	4.3	1.9	7.5	9.3	1.8
2003	2.9	4.8	1.8	8.0	9.8	1.8
2004	4.2	5.9	1.7	9.3	10.8	1.6
2005	5.4	6.9	1.5	10.3	11.8	1.4
2006	5.8	7.1	1.3	10.7	12.0	1.2
2007	3.9	5.0	1.1	8.9	10.0	1.1
2008	2.1	3.1	0.9	7.3	8.2	0.9
2009	1.4	2.2	0.8	6.6	7.3	0.7
2010	9.4	10.0	0.6	14.2	14.8	0.6
2011	11.9	12.6	0.7	16.5	17.2	0.6
2012	13.6	14.3	0.8	18.1	18.8	0.7
2013	18.9	19.8	0.9	23.2	24.0	0.8
2014	17.4	18.4	1.0	21.8	22.7	1.0
2015	19.7	20.8	1.1	24.0	25.0	1.0
2016	24.7	25.7	1.0	28.7	29.6	1.0
2017	33.6	34.5	0.9	37.1	37.9	0.9
Average difference			**1.13**			**1.07**
NIDS	15% under-reporting			20% under-reporting		
2008	-6.3	-5.4	0.9	0.0	0.8	0.8
2010	7.9	8.7	0.8	13.3	14.1	0.7
2012	11.2	12.0	0.9	16.4	17.2	0.8
2015	14.5	15.5	1.0	19.5	20.5	0.9
2017	29.5	30.4	0.9	33.7	34.5	0.8
Average difference			**0.87**			**0.82**

Figure 4.11: Comparing illicit trade estimates using population data from two different sources (AMPS data)



Notes: Error bars indicate 99% confidence intervals.

Figure 4.12: Comparing illicit trade estimates using population data from two different sources (NIDS data)



Notes: Error bars indicate 99% confidence intervals.

Alternative method to calculate CIs around annual self-reported consumption

In the main analysis, the bootstrap method was used to calculate confidence intervals around annual total consumption. Guindon, Burkhalter & Brown (2017), who used SAS, calculated confidence intervals without using the bootstrap command, which I replicated using the `total` command in Stata.

Annual cigarette consumption was calculated for each respondent by multiplying daily intensity by 365 days. Non-smokers were assigned a value of 0. Respondents who reported that they smoked, but did not report the number of cigarettes they smoked per day, were assigned the mean value of smoking intensity in that year. Annual self-reported consumption of all South Africans was calculated for each round of AMPS and NIDS using the `total` command in Stata.

The `total` command reports the estimate as a scientific expression instead of a numeric value. According to a Stata forum, the numeric format is not available for this command (Statalist: The Stata Forum, 21 October 2018). To obtain the numeric values for total annual consumption and the standard error, the `display` command was used after the `total` command. The 99% confidence intervals were calculated using the formula: total annual self-reported consumption +/- 2.576*standard error. Since the confidence intervals using this alternative method did not vary much compared to the bootstrap method (Table 4.7), the analysis was not rerun.

Table 4.7: Estimation of confidence intervals using alternative method

		Bootstrap			No bootstrap				Difference: absolute numbers			Difference: percentages		
Survey	Year	Annual self-reported consumption	99% CI Lower bound	99% CI Upper bound	Annual consumption	Standard error	99% CI Lower bound	99% CI Upper bound	Annual self-reported consumption	99% CI Lower bound	99% CI Upper bound	Annual self-reported consumption	99% CI Lower bound	99% CI Upper bound
AMPS	2002	26 308 269 778	25 257 847 282	27 358 692 274	26 308 266 598	413 239 817	25 243 760 829	27 372 772 367	3 180	14 086 452	-14 080 093	0.00	-0.06	0.05
	2003	25 557 007 025	24 475 173 506	26 638 840 545	25 557 006 084	418 206 626	24 479 705 815	26 634 306 353	941	-4 532 309	4 534 192	0.00	0.02	-0.02
	2004	26 009 543 961	24 905 420 740	27 113 675 975	26 009 547 612	433 255 498	24 893 481 449	27 125 613 775	-3 651	11 939 291	-11 937 800	0.00	-0.05	0.04
	2005	26 093 188 797	24 932 773 519	27 253 604 075	26 093 190 159	441 513 124	24 955 852 352	27 230 527 966	-1 362	-23 078 833	23 076 109	0.00	0.09	-0.08
	2006	26 518 053 483	25 302 540 897	27 733 566 069	26 518 053 660	458 374 533	25 337 280 863	27 698 826 457	-177	-34 739 966	34 739 612	0.00	0.14	-0.13
	2007	27 581 251 286	26 296 639 345	28 865 854 569	27 581 247 025	488 216 298	26 323 601 841	28 838 892 209	4 261	-26 962 496	26 962 360	0.00	0.10	-0.09
	2008	25 870 883 418	24 414 317 730	27 327 449 106	25 870 883 922	552 232 258	24 448 333 625	27 293 434 219	-504	-34 015 895	34 014 888	0.00	0.14	-0.12
	2009	26 380 901 360	25 024 937 903	27 736 873 789	26 380 902 682	507 633 713	25 073 238 237	27 688 567 127	-1 322	-48 300 334	48 306 662	0.00	0.19	-0.17
	2010	23 853 421 061	22 645 718 556	25 061 114 578	23 853 417 067	462 587 491	22 661 791 690	25 045 042 444	3 994	-16 073 134	16 072 134	0.00	0.07	-0.06
	2011	24 414 307 793	23 128 681 743	25 699 933 842	24 414 309 667	508 498 851	23 104 416 627	25 724 202 707	-1 874	24 265 116	-24 268 865	0.00	-0.10	0.09
	2012	25 978 382 238	24 747 187 201	27 209 577 275	25 978 380 146	482 393 726	24 735 733 908	27 221 026 384	2 092	11 453 293	-11 449 109	0.00	-0.05	0.04
	2013	26 297 938 839	25 105 649 172	27 490 228 506	26 297 937 293	478 595 338	25 065 075 702	27 530 798 884	1 546	40 573 469	-40 570 377	0.00	-0.16	0.15
	2014	26 509 579 572	25 286 123 011	27 733 045 302	26 509 582 903	476 386 139	25 282 412 209	27 736 753 597	-3 331	3 710 802	-3 708 295	0.00	-0.01	0.01
	2015	28 153 665 214	26 887 122 319	29 420 208 109	28 153 669 164	498 510 629	26 869 505 784	29 437 832 544	-3 950	17 616 535	-17 624 435	0.00	-0.07	0.06
NIDS	2008	22 897 894 229	20 784 417 335	25 011 371 124	22 897 893 790	836 326 737	20 743 516 115	25 052 271 465	439	40 901 219	-40 900 341	0.00	-0.20	0.16
	2010	20 871 679 832	17 503 573 783	24 239 785 881	20 871 676 890	1 293 062 004	17 540 749 168	24 202 604 612	2 942	-37 175 384	37 181 269	0.00	0.21	-0.15
	2012	22 023 188 288	19 289 606 543	24 756 770 034	22 023 189 264	1 082 064 714	19 235 790 561	24 810 587 967	-976	53 815 982	-53 817 933	0.00	-0.28	0.22
	2015	23 932 903 824	21 031 304 780	26 834 494 573	23 932 900 351	1 119 495 997	21 049 078 663	26 816 722 039	3 473	-17 773 882	17 772 534	0.00	0.08	-0.07
	2017	23 493 447 253	20 353 299 279	26 633 595 226	23 493 449 861	1 195 927 544	20 412 740 508	26 574 159 214	-2 608	-59 441 228	59 436 012	0.00	0.29	-0.22

DISCUSSION

Between 2002 and 2009, I estimated that the illicit trade in cigarettes in South Africa accounted for less than 10% of the total market, assuming 5% under-reporting of survey data. During this time, SARS investigated manufacturers suspected of evading excise and VAT payments. From 2005 to about 2009, SARS enforcement units shut down a number of manufacturers and traders involved in fraud, smuggling, and illicit manufacturing, including Mastermind Tobacco and Masters International Tobacco Manufacturing (Independent Online, 29 June 2005; Sole, 28 October 2018; Van Loggerenberg, 2019). The closing of these manufacturers, together with the very high net-of-tax prices earned by the incumbent firms, created an incentive for new entrants to enter the market. Anecdotal evidence from ex-employees at SARS suggests that these new entrants accounted for a large proportion of the increase in illicit trade from around 2009 onwards.

In 2013, SARS established Project Honey Badger to investigate the illicit trade in cigarettes (Van Loggerenberg, 2019). These investigations successfully identified cigarette manufacturers who were not paying excise taxes or VAT. However, in 2014, a ‘Rogue Unit’ disinformation campaign was launched, aimed derailing and discrediting illicit trade investigations. SARS officials were accused of a host of crimes, including spying on the then-president Jacob Zuma, operating a brothel as a front, and spying on the police service (Van Loggerenberg, 2019).

The campaign was successful, and was intrinsically linked to, and an extension of, state capture. SARS, once a professional, efficient, and progressive tax-collection agency was gutted by corruption (Van Loggerenberg, 2019). In April 2014, acting SARS commissioner Ivan Pillay wrote: ‘Our own experience has revealed that certain companies and individuals in the tobacco industry have penetrated a fragmented government system and have been using some elements and access to political parties and persons to further their own interests’ (Van Loggerenberg, 2019). When Tom Moyane was appointed as SARS Commissioner in September 2014, SARS was purged of many senior executives, including personnel who worked on enforcement and investigations (Du Toit, 26 June 2018; Kahn, 26 May 2018; Van Loggerenberg, 2019). By the end of 2015, more than 55 managers and 500 skilled staff left SARS (Van Loggerenberg, 2019). Five specialised units were disbanded; all of which were investigating the illegal cigarette trade under Project Honey Badger (Du Toit, 26 June 2018). Moyane ordered SARS officials to stop inspecting illegal factories (Van Loggerenberg, 2019).

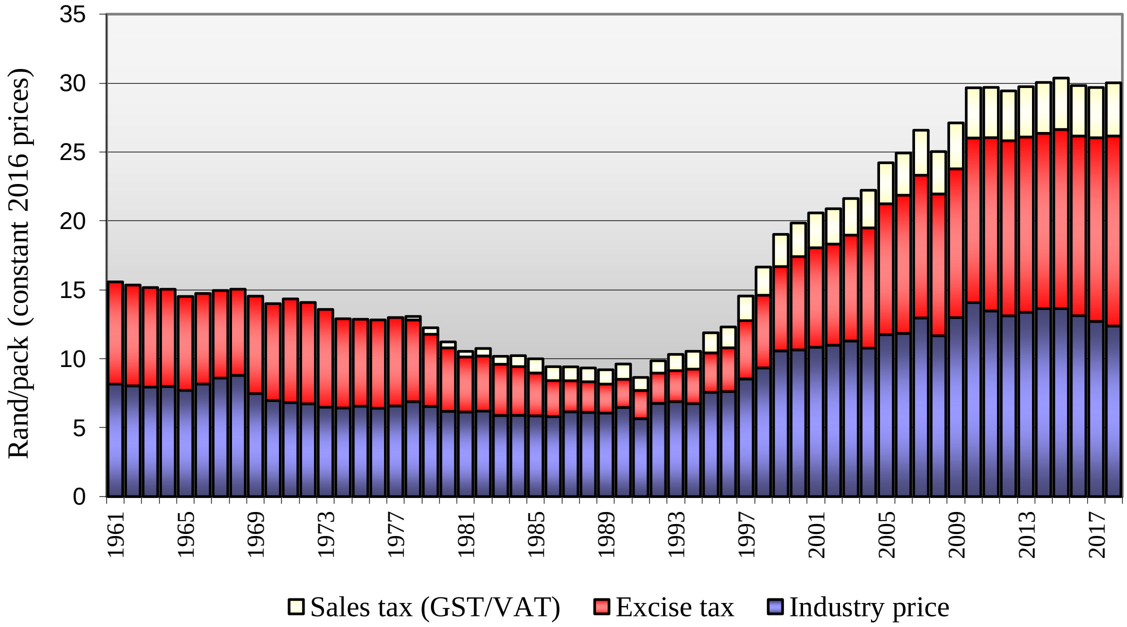
In early 2015, Project Honey Badger had 15 criminal cases against tobacco manufacturers and importers. To date (May 2022), only one of these 15 cases have resulted in a prosecution. In 2021, the director of a South African company Oakbay Trading was sentenced to 10 years in prison (South African Revenue Service, 8 December 2021). He was found guilty of falsifying export documents to not pay tax on cigarettes.

SARS's slow progress is also evident in its attempt to introduce a track-and-trace system. In April 2019, SARS issued a track-and-trace tender, announcing that it was seeking technology to enable it to curb revenue leakages caused by the illicit tobacco industry. The tender was extended four times before being cancelled by SARS Commissioner Edward Kieswetter (Mathe, 22 August 2020). Kieswetter said that those who had applied for the tender raised concerns about the nature of the tender specifications and that there were no adequate reasons for investing at the end of the tobacco value chain as opposed to the beginning or middle (Mathe, 22 August 2020).

In November 2019, the Parliamentary Monitoring Group (PMG), a group that monitors South Africa's parliamentary committees, came to the same conclusion: 'The Committee agrees with National Treasury and SARS that the increase in illicit products is as a result of weak law enforcement and tax administration challenges at SARS' (Parliamentary Monitoring Group, 20 November 2019). PMG considered submissions from various parties (including government officials, academics, the tobacco industry, and non-governmental organisations) who responded to a call from the Select Committees on Finance to comment on various taxes, including excise duties on alcohol and tobacco (Select Committees on Finance, 4 November 2019). TISA argued that the high levels of illicit trade were due to excise taxes and proposed: 'holding of excise rates at current levels for at least three years or until the illicit trade is drastically reduced' (Tobacco Institute of South Africa, 5 November 2019). TISA's comments were disingenuous since excise rates have not changed substantially in the last decade.

Figure 4.13 shows the composition of cigarettes prices, which include excise taxes, VAT, and industry prices. From 2002 to 2009, the real (inflation-adjusted) excise tax increased at an average rate of 5.7% per year (Figure 4.13). In addition to excise tax increases, the tobacco industry over-shifted the excise tax. The overall effect was a sharp increase in cigarette prices.

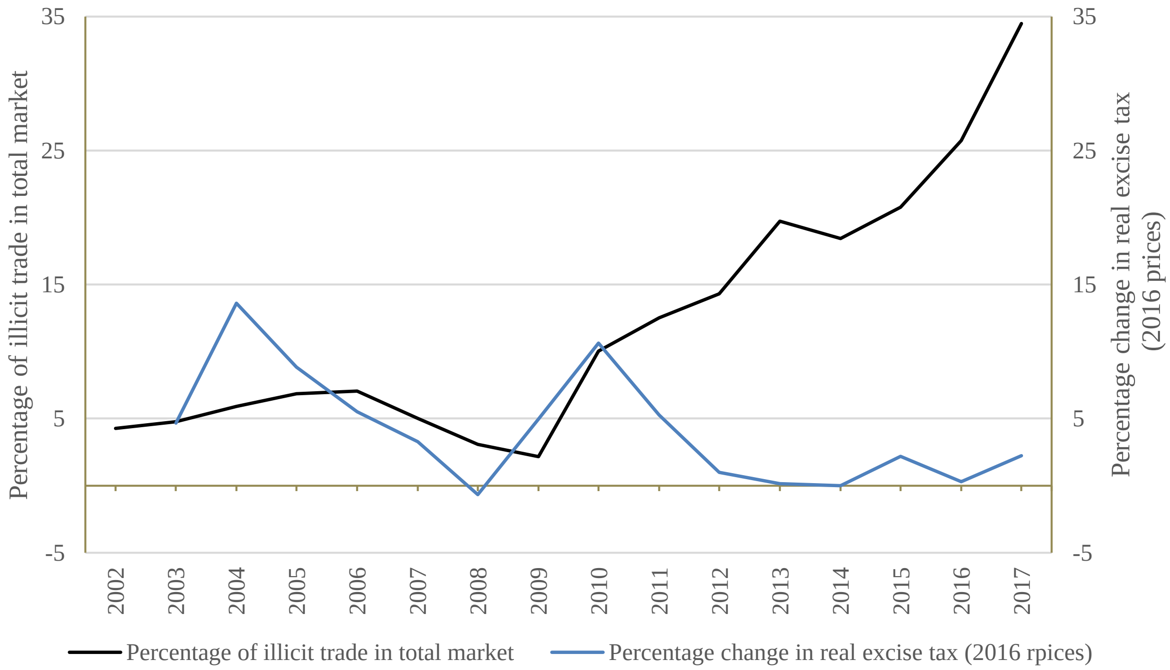
Figure 4.13: Excise tax, VAT, and industry prices: 1961−2018



Source: Van Walbeek, C. 2018. South Africa time series data for cigarettes: 1960 − 2017. [dataset]. Version1.0. Cape Town: Economics of Tobacco Control Project [producer], 2018. Cape Town: DataFirst [distributor], 2018.

The tobacco industry's argument that increases in the excise tax cause an increase in illicit trade, while sounding intuitively appealing, is not empirically supported. There is no evidence that the illicit market grew when the excise tax was increasing rapidly (Figure 4.14). Despite increasing prices, the illicit trade of cigarettes in South Africa was around 5% of the total market from 2002 to 2009, assuming 5% under-reporting of AMPS survey data. In contrast, illicit trade increased rapidly when excise taxes were relatively low: from 2009 to 2017, illicit trade increased from approximately 2% to 35%, assuming 5% under-reporting of AMPS survey data, while the real (inflation-adjusted) excise tax increased at an average rate of 2.7% per year (Figure 4.14).

Figure 4.14: Excise tax and illicit trade: 2002−2017



While SARS is aware of the illicit cigarette problem, this paper provides precise, independent estimates for 2002 to 2017. These estimates compare reasonably well with existing academic literature. For the nine years (2004 – 2012) that the current study overlaps with Van Walbeek (2014), the correlation coefficient of illicit trade estimates is 0.8 (p-value: 0.020). Using national data, Van der Zee, Van Walbeek & Magadla (2019) estimated that the illicit market comprised 31% of the total market in 2017, while Van der Zee et al. (2020) estimated that illicit trade comprised 35% of the total market among township smokers, also in 2017. These values fall within the range estimated in the current study for 2017 (30 to 35%).

The estimates of the current study are surprisingly similar to those of the industry, although the years are not the same: I estimate that illicit trade in 2017 was between 30% and 35%, while Ipsos estimated 27% in June 2018 and 33% in September 2018 (Ipsos, 2018b). It is surprising that the estimates are so close to those of the industry. Usually industry estimates are much higher than those estimated by independent researchers (Smith, Savell & Gilmore, 2013).

Illicit trade estimates in the current paper are subject to several limitations. First, the gap analysis method cannot distinguish between tax avoidance and tax evasion, and cannot determine whether illicit cigarettes are counterfeit, contraband, or illicit domestic production. However, much research has been conducted that shows that illicit domestic manufacturing is the major source of the gap between consumption and sales. This includes a recent book by an ex-SARS official (Van Loggerenberg, 2019), a thorough qualitative survey on the illicit market in South Africa and Zimbabwe (Haysom, March 2019), previous investigative journalism (Bailey, 24 November 2013), and localized surveys of townships (Van der Zee et al., 2020).

Secondly, gap analysis does not account for cigarette packs that, having paid excise tax, subsequently leave the country, for example, when people buy cigarettes in South Africa and consume them in neighboring countries. However, this is likely to be a minor issue in South Africa since legal cigarettes in most neighboring countries are similarly priced to those in South Africa. If tax-paid cigarettes leave the country, the volume (and thus the share) of illicit trade would decrease as tax-paid sales would increase while survey-based consumption would remain unchanged.

Thirdly, the comparison between cigarette consumption and legal sales is complicated by the presence of roll-your-own cigarettes that might not be included in the official statistics, but are reported as cigarette consumption during the survey. Consequently, the comparison of survey-based consumption (that includes roll-your-own cigarettes) with tax-based sales would overestimate the level of tax evasion/avoidance (Ross, 2015).

Fourthly, for AMPS, I relied on two assumptions: that smoking intensity in 2012 to 2015 remained at the 2011 estimate of 9.1 cigarettes per day, and that annual self-reported consumption in 2016 to 2017 remained at the 2015 level of 28.15 billion cigarettes. If either, or both, of these assumptions is incorrect, then the estimates of illicit trade for these years will be invalid.

Despite the limitations of the gap analysis methodology, this method is relatively simple and replicable. If data on registered sales and self-reported consumption are publicly available, researchers can obtain estimates of illicit trade without collecting primary data, which is expensive and time-consuming.

CONCLUSION

The FCTC has developed guidelines to help countries reduce the illicit trade in tobacco products, and these are detailed in *the Protocol to Eliminate Illicit Trade in Tobacco Products* (World Health Organization, 2013). This protocol was adopted in 2012, and by May 2022, 64 countries had become parties to the protocol (United Nations Treaty Collection, 2022a). Since South Africa is facing a major problem with illicit cigarettes, it should urgently become a party to the protocol. Becoming a party would allow South Africa to draw on technical assistance and international collaboration. One of the measures to control illicit trade recommended in the protocol is a track-and-trace system (discussed in the Conclusion chapter).

CHAPTER 5: Conclusion

South Africa was one of the first middle-income countries to use excise tax increases to reduce smoking prevalence, in the 1990s and early 2000s. In 1994, the government announced that it aimed to set the excise tax, which is levied as a specific tax, at a rate such that the total tax burden would equal 50% of the retail price (Linegar & Van Walbeek, 2018). This target was achieved in 1997. In 1995, the government ordered the tobacco industry to print warnings on tobacco packaging and advertising material (Republic of South Africa, 1995). The Tobacco Products Control Amendment Act of 1999, which was implemented in 2001, banned all tobacco advertising and sponsorship, prohibited smoking in all public and work places, and prohibited the distribution of free cigarettes (Republic of South Africa, 1999).

As a result of these strong policies, smoking prevalence decreased from 31% to 20% between 1995 and 2011 (South African Audience Research Foundation, 1995; South African Audience Research Foundation, 2011).

Since about 2005, the gains from the 1990s and early 2000s have waned. South Africa has not kept pace with international best practice as outlined by the FCTC (World Health Organization, 2003). The Control of Tobacco Products and Electronic Delivery Systems (CTPENDS) Bill, which was published for public comment in 2018, aims to align South African's tobacco control policy with some of the recent global developments.

In this draft bill, the Ministry of Health proposes to: (1) regulate the sale and advertising of tobacco products and electronic delivery systems, (2) regulate the packaging and appearance of tobacco products and electronic delivery systems and to make provision for the standardisation of their packaging, (3) provide standards for the manufacturing and export of tobacco products and electronic delivery systems, (4) prohibit the sale of tobacco products and electronic delivery systems to and by persons under the age of 18 years, (5) prohibit the free distribution of tobacco products and electronic delivery systems, and (6) prohibit the sale of tobacco products and electronic delivery systems by means of vending machines (Republic of South Africa: Department of Health, 9 May 2018). Although this bill is more than four years old, it has not yet gone through the legislative process to become law. The aim of the draft bill is to reduce the demand for cigarettes.

While the CTPENDS bill includes plain packaging, the exact requirements (including which graphic health warnings should be used) is not yet determined. A set of warnings for immediate use is crucial in order that the implementation of plain packaging not be further delayed. Senkubuge (2020) found that the most effective warnings were lung cancer, gangrene, impotence, abortion, and oral disease. A second set of health warnings should be ready so that they are refreshed on a regular basis. In most countries, warnings are not refreshed frequently enough, which leads to reduced impact over time (Cunningham, 2022). Australia and Canada have gone a decade without changing warning requirements (Cunningham, 2022). In contrast, Ecuador, Colombia, Mexico, Panama and Uruguay have had nine or more rounds of picture warnings (Cunningham, 2022).

Reducing the demand for cigarettes can be done by ensuring that people do not start smoking, and by reducing demand among smokers (either by smokers quitting or by them smoking less). The aim of this thesis was to investigate quitting behaviour in South Africa. To do this, I estimated the effect of prices on smoking cessation, assessed the effectiveness of plain packaging on smokers and non-smokers, and estimated the size of the illicit market.

Effect of prices on smoking cessation

Between 1995 and 2017, the real (inflation-adjusted) excise tax increased at an average rate of 7.2% per year (Van Walbeek, 2018). The largest tax growth occurred between 1995 and 2011, when the real excise tax increased at an average rate of 9.7% per year (Van Walbeek, 2018). Between 2011 and 2017, the real excise tax per pack of 20 cigarettes increased by an average rate of only 1% per year (Van Walbeek, 2018).

The results from chapter 2 indicate that tax-led increases in the retail price resulted in higher rates of smoking cessation. A 10% increase in the price of cigarettes was estimated to result in a 5.5% to 8.6% increase in the probability of quitting. Most of these gains occurred in the 1990s and early 2000s when cigarette prices were increasing rapidly as a result of the combination of excise tax increases and the tobacco industry's over-shifting of taxes.

In his 2022 budget speech, the finance minister, Enoch Godongwana, announced that the excise tax on a pack of 20 cigarettes would increase by 5.5% (from R18.79 to R19.82) (Republic of South Africa, 23 February 2022). Over the same period, inflation increased by 4.5%. Given the negligible tax increase, it is unlikely that the increase will have any effect on cigarette demand. This small rate of change has happened repeatedly in the past decade, illustrating that the government has abandoned using excise tax increases as an effective tobacco control tool.

The tobacco industry, and BAT in particular, constantly argue that higher cigarette taxes lead to an increase in illicit trade (British American Tobacco, 24 February 2021). Results from chapter 4 indicate that there is no evidence that the illicit market grew when the excise tax was increasing rapidly. Moreover, the pricing strategy of BAT from 1990s to 2000s casts doubt on the authenticity of their argument. It is disingenuous to contend that higher prices from higher taxes lead to increased illicit trade but not higher prices imposed by manufacturers. The very high net-of-tax prices earned by BAT created an incentive for new manufacturers to enter the market in the late 2000s (Van Walbeek & Filby, 20 September 2021). As a result, BAT lost substantial market share from 2010 and it was no longer viable for it to overshift excise taxes (Van Walbeek & Filby, 20 September 2021).

Increasing excise taxes should be done in tandem with establishing efficient systems to curb illicit trade. While the illicit cigarette trade in South Africa is a serious problem, its presence should not be used to undermine excise tax increases, since the underlying cause is weak tax administration, not the tax level.

Effectiveness of plain packaging

In the third chapter, I investigated the intention among smokers to buy cigarettes, the intention among non-smokers to try cigarettes, and perceptions of harm among smokers and non-smokers. Results indicate that plain packaging would be effective in reducing people's utility from cigarettes. I found that smokers reported preferring not to buy plain packs and non-smokers preferred not to try plain packs. In terms of health risk, both smokers and non-smokers perceived plain packs to be the most risky to health.

South Africa is far behind other countries when it comes to health warnings on cigarette packs. As of October 2021, 134 countries or jurisdictions had graphic health warnings (GHWs) on cigarette packs, while South Arica still only has text warnings (Cunningham, 2022). In terms of the size of health warnings, from largest to smallest (text or GHW), South Africa ranked 158 out of 206 countries/jurisdictions (Canadian Cancer Society, October 2021).

Aside from lagging behind other countries, South Africa has not fulfilled its international obligations under the FCTC. Each Party is meant to implement health warning requirements within the three years after the WHO FCTC comes into force for that Party. For South Africa, this deadline was 18 July 2008 (Republic of South Africa: Department of Health, 9 May 2018). Manufacturers are currently only required to print a heath warning that covers 20% of the front of the pack and 30% of back of the pack (Republic of South Africa, 1995). The WHO FCTC Article 11 (Packaging and labelling of tobacco products) guidelines propose adopting measures to restrict or prohibit the use of logos, colours, brand images, or promotional information on packaging, other than brand and product names displayed in a standard colour and font style (plain packaging) (World Health Organization, 2008a). Article 11 guidelines also recommend health warnings on individual sticks: 'Parties should consider introducing other innovative measures regarding location, including, but not limited to, requiring health warnings and messages to be printed on the filter overwrap portion of cigarettes' (World Health Organization, 2008a). Placing warnings on individual sticks has not been implemented in any country thus far (May 2022). While some countries, like the UK and Canada, are considering it, it is not yet being considered in South Africa.

Countries that have implemented plain packaging transitioned from packs with GHWs to plain packs (which all include GHWs). South Africa is proposing to move directly from written health warnings to plain packaging with GHWs. This one-step move would be unprecedented. The results from chapter 3 indicate that the demand for cigarettes would be reduced if South Africa implemented plain packaging and health warnings on individual sticks.

Size of the illicit market

Tax evasion is a significant problem in South Africa. The illicit market was estimated at around 30%−35% of the total market in 2017. Since manufacturers of illicit cigarettes do not pay excise or VAT, illicit cigarettes are sold at much lower prices than legal cigarettes. If smokers of legal brands find that their preferred legal brand is too expensive, they can easily switch to illicit brands, which are easily accessible, and there are many illicit brands to choose from.

Between 2002 and 2009, the illicit cigarette market accounted for around 5% of the total market. Since 2009, the illicit cigarette market increased sharply. I found no evidence that excise tax increases were linked to an increase in illicit trade. When excise taxes were increasing rapidly, illicit trade was stable (2002−2009). On the other hand, when excise tax increases were relatively modest, illicit trade increased rapidly (2009−2017).

A decade ago, SARS announced that one of its main compliance activities for 2012/13 – 2016/17 was to 'Improve authentication markings on cigarettes to enable identification of legal cigarettes' (South African Revenue Service, 2012). Ten years later, no progress has been made. The obsolete diamond stamp, which does not provide any assurance that duty has been paid, is still used. A number of die stamps issued to the tobacco industry are unaccounted for, and the mark itself is easily counterfeited (World Bank, 2019). The management crisis at SARS that resulted in the closing of the special investigative units and the loss of experienced personnel is documented in the discussion of chapter 4.

Although SARS re-established the Illicit Economy Unit in August 2018 (South African Revenue Service, 24 August 2018), illicit trade remains widespread. SARS achieved some level of success in reducing the illicit cigarette market in 2019 (Van Walbeek C, Van der Zee K & Vellios N, 5 March 2020). In January 2020, SARS announced that, since April 2019, the unit had recovered R2.6 billion in taxes (from tobacco smuggling, illegal imports, and counterfeit goods) (fin24, 24 January 2020). However, the illicit market was firmly entrenched by the end of the Covid-19 sales ban (27 March 2020 – 17 August 2020) (Van der Zee, Filby & Van Walbeek, 2022).

In the 2022 budget speech, the finance minister spoke about illicit trade and SARS's achievements: 'We are also dealing with illicit trade. Just yesterday [22 February 2022], SARS conducted a search and seizure operation. This operation uncovered another consignment of illegal tobacco products, bringing the total value of illicit tobacco seized during the pandemic to over R350 million. Overall, SARS has raised assessments of R18 billion additional duties, cancelled the trading licenses of 3 operators, liquidated one operator, and referred 8 cases for criminal prosecution' (Republic of South Africa, 23 February 2022). No mention was made of a track-and-trace system. Although SARS issued a track-and-trace tender in April 2019, it was cancelled after being extended four times (Mathe, 22 August 2020).

A track-and-trace system independent of the tobacco industry would be likely to reduce illicit cigarette trade. A track-and-trace system introduced in Kenya resulted in a 49% increase in legitimate cigarette and cigar sales from 2013 to 2015 (Ross, 2017). In April 2013, Kenya selected SICPA to set up the excisable goods management system for tobacco and alcohol products, which allows for production counting, track-and-trace, stock control, tax forecasting, the forecasting and processing of tax stamps, and collecting other business intelligence. The excisable goods management system facilitates the detection of counterfeit goods, prevents smuggling, and eliminates the falsification of production volumes.

A track-and-trace system would allow SARS to track cigarettes from manufacturer to retailer. Controls on the cigarette supply chain would help to eliminate tax evasion. Tighter enforcement would deter retailers from selling cigarettes without paying excise tax and VAT. However, simply appointing a company will not solve the problem unless the company is closely monitored by SARS, and relations between SARS and the new company are free of corruption. In the past, many illicit manufacturers have faced no consequences for their illegal behaviour, a fact which has fueled the illicit market (Van Loggerenberg, 2019). A high degree of probability of being caught and prosecuted, together with stiff penalties, needs to be the norm.

Contribution to the existing literature

Chapter 2 provided the first analysis of the impact of prices on tobacco cessation in South Africa. This chapter contributes to the growing literature on smoking cessation in low-income and middle-income countries (Gonzalez-Rozada & Montamat, 2019; Kenkel, Lillard & Liu, 2009; Kostova, Husain & Chaloupka, 2017; Ross et al., 2014). I have provided a thorough methodology for how survival analysis techniques are applied to smoking cessation. The same techniques apply to smoking onset. The explanation of these methods and their application to national data can be used by researchers in other countries to conduct similar analyses of smoking onset and cessation.

Chapter 3 provided results from an experiment and an auction. Only two existing papers (Giang et al., 2016; Kotnowski et al., 2016) included price as an attribute in their experiments, and only one paper (Kotnowski et al., 2016) evaluated plain packaging and price. Given the importance of price in any purchase decision, this chapter is an important contribution to the limited literature that investigates plain packaging in a discrete choice framework. While there are some papers (Drovandi et al., 2019a; Drovandi et al., 2019b; Gallopel-Morvan, Droulers & Pantin-Sohier, 2019; Hoek et al., 2016; Lund & Scheffels, 2018; Mitchell et al., 2021; Moodie et al., 2020) that investigate warnings on individual sticks, none of these include warnings on individual cigarettes as an attribute in a discrete choice framework.

The gap analysis provided illicit trade estimates for South Africa from 2002 to 2017, building on the work of Blecher (2010). The current gap analysis differs from Blecher's (2010) paper in the following ways: (1) two datasets were used, whereas Blecher used one, (2) Blecher (2010) did not add imported cigarettes to registered sales, (3) the time period of the current analysis covered 16 years (compared to 11 years in Blecher (2010)), (4) confidence intervals were created around smoking prevalence and smoking intensity, whereas Blecher (2010) did not include confidence intervals, (5) both trends and actual estimates were reported, whereas Blecher (2010) reports actual estimates only, and (6) raw data were used in the my analysis, whereas Blecher (2010) only had access to aggregated library data. The gap analysis provided two ways of estimating confidence intervals: (1) bootstrapping the point estimate of the product of smoking status and smoking intensity (using Stata), and (2) estimating total annual self-reported consumption (using Stata) and then calculating confidence intervals manually.

Avenues for future research

1. The determinants of smoking cessation using survival analysis techniques can be applied to other LMICs. Researchers will require a long series of price/excise tax data. Researchers should check whether there is sufficient variation in price/tax data. Pseudo-longitudinal data can be created from cross-sectional datasets, provided that respondents were asked about the age or year of smoking onset and cessation. Surveys that also include birth date and interview date will allow researchers to bound the interval that a person could have started or quit smoking to a 12-month period.
2. Researchers could investigate alternative designs to the current flip-top pack. Some countries now require a minimum surface area for warnings, in addition to a minimum percentage size (e.g., Australia and New Zealand) (Cunningham, 2022). In Canada, a pack of 20 cigarette is required to have a minimum warning surface area 43.6 cm^2 of the front and back of the pack. Canada requires cigarettes, effective from February 2022, to be sold in the slide and shell package format, which increases surface area over that of the flip top (Cunningham, 2022)
3. The gap analysis (chapter 4) can be updated when the results from 2021 Global Adult Tobacco Survey South Africa (GATS SA) are released by the Centre for Disease Control. The GATS SA survey included questions on smoking prevalence and smoking intensity, which are necessary for the gap analysis. While using the same survey (AMPS or NIDS) would have been preferable, neither of these surveys has been done since 2015 (for AMPS) or since 2017 (for NIDS).
4. In the introduction, I noted that the affordability of cigarettes in South Africa has remained unchanged for the past two decades. This statement was made from my own calculations based on data from South African Reserve Bank (2022) and time-series data from Van Walbeek (2018). A more thorough investigation on the affordability of cigarettes is warranted. The WHO notes that the share of tax in the retail price is not enough to ensure that excise tax increases will be successful in reducing demand (World Health Organization, 2021b). A tax share can be high while, at the same time, tobacco products remain affordable. Affordability indices can be calculated by taking the nominal price of cigarettes (multiplied by 100 to get price of 2000 cigarettes) divided by the nominal per capita GDP for each year.

5. Researchers could investigate the proportion of the population who can distinguish a legal pack from an illegal pack, and whether smokers would still buy illegal cigarettes if they knew that they were illegal. This research may help in designing information campaigns to educate the public on how to identify illicit packs. Assuming fewer people would buy illicit cigarettes, the proportion of illicit trade would decrease.

Policy recommendations

Based on the conclusions of this thesis, policymakers should consider the following:

1. **Increase the excise tax on tobacco products.** While there is a substantial illicit trade problem, Treasury should not buy the self-interested argument of the tobacco industry that higher excise taxes results in higher illicit trade.
2. **Implement plain packaging of all tobacco products.** The CTPENDS bill, which includes plain packaging, should be passed into law.
3. **Enforce the ban on the sale of single cigarettes.** Legislation exists that bans the sale of single cigarettes. However, the ban is not enforced. For plain packaging to be effective, all smokers need to see the pack
4. **Implement a track-and-trace system.** A track-and-trace system, independent of the tobacco industry and its proxies, would ensure that all products manufactured in South Africa are accounted for.
5. **Ratify the FCTC's Protocol to Eliminate Illicit Trade in Tobacco Products.** Joining the group of more than 64 countries (United Nations Treaty Collection, 2022a) that are currently (May 2022) parties to the Protocol would allow South Africa to draw on technical assistance from other countries.
6. **Strengthen oversight institutions**, particularly within SARS.

REFERENCES

Action on Smoking and Health. 13 June 2021. Bill to put health warnings on cigarette sticks being put to Parliament on Monday 14th June. https://web.archive.org/web/20220513132601/https://ash.org.uk/about-ash/all-party-parliamentary-group-on-smoking-health/press-releases-all-party-parliamentary-group-on-smoking-health/bill-to-put-health-warnings-on-cigarette-sticks-being-put-to-parliament-on-monday-14th-june/. [2022, May 13].

Akaike, H. 1974. A new look at the statistical model identification. *IEEE Transactions on Automatic Control.* 19(6):716-723. DOI:10.1109/TAC.1974.1100705.

Allison, P.D. 1984. Event History Analysis: Regression for Longitudinal Event Data. California: Sage Publications: Issue 46.

Anderson, B. & Phillips, H. 2006. Adult mortality (age 15−64) based on death notification data in South Africa: 1997−2004. https://www.statssa.gov.za/publications/Report-03-09-05/Report-03-09-052004.pdf. [2019, May 10].

Australian Government. July 2013. Competition and Consumer (Tobacco) Amendment (Rotation of Health Warnings). Information Standard F2013C00598. https://www.legislation.gov.au/Details/F2013C00598. [2022, May 13].

Australian Government: Department of Health. 2014a. Tobacco Plain Packaging. https://www1.health.gov.au/internet/main/publishing.nsf/Content/822B369C0196CB1CCA257D140082A22F/$File/TPP%20Your%20Guide%20(Low%20Res).PDF. [2019, Apr 2].

Australian Government: Department of Health. 2014b. Tobacco plain packaging: non-cigarette tobacco products. https://www.health.gov.au/resources/publications/tobacco-plain-packaging-your-guide-supplement-non-cigarette-tobacco-products. [2022, May 13].

Babineau, K. & Clancy, L. 2015. Young people's perceptions of tobacco packaging: a comparison of EU Tobacco Products Directive & Ireland's Standardisation of Tobacco Act. *BMJ Open.* 5(6):e007352. DOI:10.1136/bmjopen-2014-007352.

Bailey, C. 24 November 2013. Sars to clamp down on tobacco companies. Independent Online. https://web.archive.org/web/20181012110517/https://www.iol.co.za/business-report/companies/sars-to-clamp-down-on-tobacco-companies-1611521. [2018, Oct 22].

Bansal-Travers, M., Hammond, D., Smith, P. & Cummings, K.M. 2011. The impact of cigarette pack design, descriptors, and warning labels on risk perception in the U.S. *American Journal of Preventive Medicine.* 40(6):674-682. DOI:10.1016/j.amepre.2011.01.021.

Barrientos-Gutierrez, I., Islam, F., Cho, Y.J., Salloum, R.G., Louviere, J., Arillo-Santillán, E., Reynales-Shigematsu, L.M., Barnoya, J. et al. 2021. Assessing cigarette packaging and labelling policy effects on early adolescents: results from a discrete choice experiment. *Tobacco Control.* 30(5):505. DOI:10.1136/tobaccocontrol-2019-055463.

Becker, G.M., Degroot, M.H. & Marschak, J. 1964. Measuring utility by a single-response sequential method. *Behavioral Science.* 9(3):226-232. DOI:10.1002/bs.3830090304.

Becker, G.S. & Murphy, K.M. 1988. A Theory of Rational Addiction. *Journal of Political Economy.* 96(4):675-700. DOI:10.1086/261558.

Blecher, E. 2010. A mountain or a molehill: Is the illicit trade in cigarettes undermining tobacco control policy in South Africa? *Trends in Organized Crime.* 13:299-315. DOI:10.1007/s12117-010-9092-y.

Blecher, E. & Drope, J. 2014. The rewards, risks and challenges of regional tobacco tax harmonisation. *Tobacco Control.* 23(e1):e7. DOI:10.1136/tobaccocontrol-2013-051241.

Blecher, E., Liber, A., Ross, H. & Birckmayer, J. 2015. Euromonitor data on the illicit trade in cigarettes. *Tobacco Control.* 24(1):100. DOI:10.1136/tobaccocontrol-2013-051034.

Boachie, M.K., Rossouw, L. & Ross, H. 2021. The Economic Cost of Smoking in South Africa, 2016. *Nicotine Tob Res.* 23(2):286-293. DOI:10.1093/ntr/ntaa162.

Box-Steffensmeier, J. & Jones, B. 2004. *Event History Modeling: A Guide for Social Scientists.* Cambridge: Cambridge University PressDOI:DOI: 10.1017/CBO9780511790874.

British American Tobacco. 24 February 2021. *Tobacco tax hike is a dangerous mistake, warns BATSA. https://web.archive.org/web/20210510064906/http://www.batsa.co.za/group/sites/BAT_A2ELAD.nsf/vwPagesWebLive/DOBYJKZU/$FILE/Tobacco_tax_hike_is_a_dangerous_mistake,_warns_BATSA.pdf?openelement*.

Business Day. 1 March 2017. BAT threatens to close SA's only cigarette plant due to branding regulations. [2022, May 13].

Business Day. 14 October 2019. Sars to quantify size of illicit economy in coming months, says Tito Mboweni. https://www.businesslive.co.za/bd/national/2019-10-14-sars-to-quantify-size-of-illicit-economy-in-coming-months-says-tito-mboweni/. [2020, 23 Jan].

Camilleri, L. 2019. History of survival analysis. https://www.um.edu.mt/library/oar/bitstream/123456789/55748/1/History%20of%20Survival%20Analysis.pdf. *The Sunday Times of Malta.* Available: [2022, May 13].

Campaign for Tobacco-Free Kids. 27 January 2020. *Reminder/Alert on Euromonitor. Email recipient: Nicole Vellios (and all members of the Framework Convention Alliance email list)*.

Canadian Cancer Society. October 2021. Cigarette Package Health Warnings: International status report. Seveth Edition. https://cdn.cancer.ca/-/media/files/about-us/media-releases/2021/cigarette-health-warnings-report/ccs-international-warnings-report-2021.pdf?_ga=2.63531564.244926713.1641298469-393367043.1641298469. [2022, May 14].

Cawley, J., Markowitz, S. & Tauras, J. 2004. Lighting up and slimming down: the effects of body weight and cigarette prices on adolescent smoking initiation. *J Health Econ.* 23(2):293-311. DOI:10.1016/j.jhealeco.2003.12.003.

Central Statistical Service. 9 April 1987. Mid-year estimate: 1970−1986. http://www.statssa.gov.za/publications/P0302/P03021986.pdf. [2022, May 13].

Cornell Statistical Consulting Unit. 2020. Overlapping Confidence Intervals and Statistical Significance Statnews #73. https://cscu.cornell.edu/wp-content/uploads/73_ci.pdf. [2022, May 13].

Cox, D. 1972. Regression models and life-tables. *Journal of the Royal Statistical Society.* Series B(34):187−220. DOI:10.1111/j.2517-6161.1972.tb00899.x.

Cunningham, R. 2022. Tobacco package health warnings: a global success story. *Tobacco Control.* 31(2):272. DOI:10.1136/tobaccocontrol-2021-056560.

De Bekker-Grob, E., Ryan, M. & Gerard, K. 2012. Discrete choice experiments in health economics: a review of the literature. *Health Economics.* 21(2):145-172. DOI:10.1002/hec.1697.

Debrott Sánchez, D. 2006. Economía del Control del Tabaco en los Países del Mercosur y Estados Asociados: Chile. Washington, DC: Organización Panamericana de la Salud.

Deloitte. May 2011. Tobacco packaging regulation: An international assessmmet of the intended and unintended consequences.

https://web.archive.org/web/20220315091902/https://www.bat.com/group/sites/UK__9D9KCY.nsf/vwPagesWebLive/DO8GHFEN. [2022, May 13].
Demographic and Health Survey. 2016. South Africa [dataset]. Version 1. Pretoria: NDoH, SAMRC, and Statistics SA [producers], 2019. Rockville: DHS Program [distributors], 2019.
Dietz, P.M., Homa, D., England, L.J., Burley, K., Tong, V.T., Dube, S.R. & Bernert, J.T. 2011. Estimates of Nondisclosure of Cigarette Smoking Among Pregnant and Nonpregnant Women of Reproductive Age in the United States. *American Journal of Epidemiology.* 173(3):355-359. DOI:10.1093/aje/kwq381.
Douglas, S. 1998. The Duration of the Smoking Habit. *Economic Inquiry.* 36(1):49-64. DOI:10.1111/j.1465-7295.1998.tb01695.x.
Douglas, S. & Hariharan, G. 1994. The hazard of starting smoking: estimates from a split population duration model. *J Health Econ.* 13(2):213-230. DOI:10.1016/0167-6296(94)90024-8.
Drovandi, A., Teague, P.-A., Glass, B. & Malau-Aduli, B. 2019a. Smoker perceptions of health warnings on cigarette packaging and cigarette sticks: A four-country study. *Tob Induc Dis.* 17(March). DOI:10.18332/tid/104753.
Drovandi, A., Teague, P.-A., Glass, B. & Malau-Aduli, B. 2019b. Do health warnings on cigarette sticks dissuade smokers and non-smokers? A focus group and interview study of Australian university students. *Psychology research and behavior management.* 12:361-373. DOI:10.2147/PRBM.S193754.
Drovandi, A., Teague, P.-A., Glass, B. & Malau-Aduli, B. 2019c. A systematic review of the perceptions of adolescents on graphic health warnings and plain packaging of cigarettes. *Systematic Reviews.* 8(1):25. DOI:10.1186/s13643-018-0933-0.
Du Toit, P. 26 June 2018. Sars Is A Mess Thanks To Tom Moyane. Here's How He Did It. Huffington Post. https://www.huffingtonpost.co.za/2018/03/20/the-damage-tom-moyane-wrought-on-sars_a_23390102/. [2019, Mar 10].
Edwards, S.A., Bondy, S.J., Kowgier, M., McDonald, P.W. & Cohen, J.E. 2010. Are Occasional Smokers a Heterogeneous Group? An Exploratory Study. *Nicotine & Tobacco Research.* 12(12):1195-1202. DOI:10.1093/ntr/ntq168.
Euromonitor International. *Cigarettes in South Africa. July 2017.*
Fair-Trade Independent Tobacco Association. May 2018. Press release. https://web.archive.org/save/http://fita.co.za/press-release-fita-for-immediate-release-2/. [2022, May 13].
Fair-Trade Independent Tobacco Association. November 2017. Public interest has BAT running scared. https://web.archive.org/web/20220315083246/http://fita.co.za/public-interest-has-bat-running-scared/. [2022, May 13].
Farnworth, M., G,. 2006. What Motivates Daily Cigarette Smokers To Quit? Retrospective Annual Discrete Duration Analysis. *Substance Use & Misuse.* 41(4):533-554. DOI:10.1080/10826080500521623.
Filby, S., van der Zee, K. & van Walbeek, C. 2021. The temporary ban on tobacco sales in South Africa: lessons for endgame strategies. *Tobacco Control.* 10.1136/tobaccocontrol-2020-056209:tobaccocontrol-2020-056209. DOI:10.1136/tobaccocontrol-2020-056209.
fin24. 24 January 2020. Kieswetter: SARS' illicit economy unit has recovered R2.6bn so far. https://web.archive.org/save/https://www.fin24.com/Economy/kieswetter-sars-illicit-economy-unit-has-recovered-r26bn-so-far-20200124-3. Available: https://web.archive.org/save/https://www.fin24.com/Economy/kieswetter-sars-illicit-economy-unit-has-recovered-r26bn-so-far-20200124-3 [2020, Feb 12].

Flanangan, R. 30 October 2018. Cancer warning on every cigarette? Canada's considering it. CTVNews. https://www.ctvnews.ca/health/cancer-warning-on-every-cigarette-canada-s-considering-it-1.4156033. [2019, Apr 2].

Forster, M. & Jones, A. 2001. The role of tobacco taxes in starting and quitting smoking: Duration analysis of British data. *Journal of the Royal Statistical Society.* 164(Part 3):517-547. DOI:10.1111/1467-985X.00217.

Francis, D.B., Mason, N., Ross, J.C. & Noar, S.M. 2019. Impact of tobacco-pack pictorial warnings on youth and young adults: A systematic review of experimental studies. *Tob Induc Dis.* 17:41. DOI:10.18332/tid/108614.

Gagné, T. 2017. Estimation of smoking prevalence in Canada: Implications of survey characteristics in the CCHS and CTUMS/CTADS. *Canadian Journal of Public Health.* 108(3):e331–e334. DOI:10.17269/cjph.108.5895.

Gallagher, A. & Gilmore, A. 8 April 2019. Euromonitor International now accepts tobacco industry funding: a win for PMI at the expense of research on the tobacco industry. *Tob Control.* Blog.

Gallagher, A., Evans-Reeves, K., Hatchard, J. & Gilmore, A. 2018. Tobacco industry data on illicit tobacco trade: a systematic review of existing assessments. *Tobacco Control.* 0:1–12. DOI:10.1136/tobaccocontrol-2018-054295.

Gallet, C.A. & List, J.A. 2003. Cigarette demand: a meta-analysis of elasticities. *Health Econ.* 12(10):821-835. DOI:10.1002/hec.765.

Gallopel-Morvan, K., Droulers, O. & Pantin-Sohier, G. 2019. Dissuasive cigarettes: which cues are the most effective at deterring young people from smoking? *Public Health.* 174:22-30. DOI:10.1016/j.puhe.2019.05.034.

García-Rodríguez, O., Secades-Villa, R., Flórez-Salamanca, L., Okuda, M., Liu, S.-M. & Blanco, C. 2013. Probability and predictors of relapse to smoking: results of the National Epidemiologic Survey on Alcohol and Related Conditions (NESARC). *Drug and alcohol dependence.* 132(3):479-485. DOI:10.1016/j.drugalcdep.2013.03.008.

Gelman, A. & Hill, J. 2007. *Data Analysis using Regression and Multilevel/Hierarchical Models.* Cambridge; New York: Cambridge University Press.

Gendall, P., Eckert, C., Hoek, J. & Louviere, J. 2018. Estimating the effects of novel on-pack warnings on young adult smokers and susceptible non-smokers. *Tobacco Control.* 27(5):519. DOI:10.1136/tobaccocontrol-2017-053719.

Giang, K.B., Chung, L.H., Minh, H.V., Kien, V.D., Giap, V.V., Hinh, N.D., Cuong, N.M., Manh, P.D. et al. 2016. Relative Importance of Different Attributes of Graphic Health Warnings on Tobacco Packages in Viet Nam. *Asian Pacific Journal of Cancer Prevention.* 17(S1):79-84. DOI:10.7314/APJCP.2016.17.S1.79.

Gilmore, A.B., Fooks, G., Drope, J., Bialous, S., A., & Jackson, R.R. 2015. Exposing and addressing tobacco industry conduct in low-income and middle-income countries. *The Lancet.* 385(9972):1029-1043. DOI:10.1016/S0140-6736(15)60312-9.

Gonzalez-Rozada, M. & Montamat, G. 2019. How Raising Tobacco Prices Affects the Decision to Start and Quit Smoking: Evidence from Argentina. *International journal of environmental research and public health.* 16(19):3622. DOI:10.3390/ijerph16193622.

Government of Canada: Health Canada. 10 June 2022. News release: Government of Canada proposes to print health warnings on individual cigarettes. https://www.canada.ca/en/health-canada/news/2022/06/government-of-canada-proposes-to-print-health-warnings-on-individual-cigarettes.html.

Guindon, G.E. 2014. The impact of tobacco prices on smoking onset: a methodological review. *Tobacco Control.* 23(2):e5. DOI:10.1136/tobaccocontrol-2012-050496.

Guindon, G.E., Burkhalter, R. & Brown, K.S. 2017. Levels and trends in cigarette contraband in Canada. *Tobacco Control.* 26(5):518. DOI:10.1136/tobaccocontrol-2016-052962.

Guindon, G.E., Paraje, G.R. & Chávez, R. 2018. Prices, inflation, and smoking onset: the case of Argentina. *Economic Inquiry.* 56(1):424-445. DOI:10.1111/ecin.12490.
Guindon, G.E., Paraje, G.R. & Chaloupka, F.J. 2019. Association of Tobacco Control Policies With Youth Smoking Onset in Chile. *JAMA Pediatr.* 173(8):754-762. DOI:10.1001/jamapediatrics.2019.1500.
Gujarati, D. 2003. *Basic econometrics.* New York: McGraw-Hill.
Hammond, D. & Parkinson, C. 2009. The impact of cigarette package design on perceptions of risk. *J Public Health (Oxf).* 31(3):345-353. DOI:10.1093/pubmed/fdp066.
Hammond, D., Dockrell, M., Arnott, D., Lee, A. & McNeill, A. 2009. Cigarette pack design and perceptions of risk among UK adults and youth. *Eur J Public Health.* 19(6):631-637. DOI:10.1093/eurpub/ckp122.
Hammond, D., White, C., Anderson, W., Arnott, D. & Dockrell, M. 2014. The perceptions of UK youth of branded and standardized, 'plain' cigarette packaging. *Eur J Public Health.* 24(4):537-543. DOI:10.1093/eurpub/ckt142.
Hardin, J., W,. 2005. Generalized Estimating Equations. In *Encyclopedia of Statistics in Behavioral Science.* DOI:10.1002/0470013192.bsa250.
Harris, J.E., Ares, G., Gerstenblüth, M., Machin, L. & Triunfo, P. 2017. Impact of plain packaging of cigarettes on the risk perception of Uruguayan smokers: an experimental study. *Tobacco Control.* 10.1136/tobaccocontrol-2017-053639. DOI:10.1136/tobaccocontrol-2017-053639.
Hauber, A.B., González, J.M., Groothuis-Oudshoorn, C.G., Prior, T., Marshall, D.A., Cunningham, C., MJ, I.J. & Bridges, J.F. 2016. Statistical Methods for the Analysis of Discrete Choice Experiments: A Report of the ISPOR Conjoint Analysis Good Research Practices Task Force. *Value Health.* 19(4):300-315. DOI:10.1016/j.jval.2016.04.004.
Haysom, S. March 2019. *The Illicit Tobacco Trade in Zimbabwe and South Africa: Impacts and Solutions*. [2020, 13 Februrary].
Her Majesty's Revenue and Customs. 5 March 2020. *Freedom of Information ref: FOI2020/00359.* United Kingdom.
Her Majesty's Revenue and Customs. 14 June 2018. Measuring tax gaps 2018 edition: Methodological annex. https://www.gov.uk/government/statistics/measuring-tax-gaps. [2018, Oct 18].
Her Majesty's Revenue and Customs. 20 June 2019. Measuring tax gaps 2019 edition: Tax gaps estimates for 2017-18. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/820979/Measuring_tax_gaps_2019_edition.pdf. [2020, Jan 23].
Hess, W. & Persson, M. 2012. The duration of trade revisited. *Empirical Economics.* 43(3):1083-1107. DOI:10.1007/s00181-011-0518-4.
Hoek, J., Gendall, P., Eckert, C. & Louviere, J. 2016. Dissuasive cigarette sticks: the next step in standardised ('plain') packaging? *Tobacco Control.* 25(6):699. DOI:10.1136/tobaccocontrol-2015-052533.
Hoffman, S.D. & Duncan, G.J. 1988. Multinomial and conditional logit discrete-choice models in demography. *Demography.* 25(3):415-427. DOI:10.2307/2061541.
Iglesias, R.M., Szklo, A.S., Souza, M.C. & de Almeida, L.M. 2017. Estimating the size of illicit tobacco consumption in Brazil: findings from the global adult tobacco survey. *Tobacco Control.* 26(1):53. DOI:10.1136/tobaccocontrol-2015-052465.
Independent Online. 29 June 2005. Cigarette firm accused of defrauding taxman. https://web.archive.org/web/20181029105107/https://www.iol.co.za/news/south-africa/cigarette-firm-accused-of-defrauding-taxman-245099. [2019, May 2].

International Agency for Research on Cancer. 2011. *IARC Handbooks of Cancer Prevention, Tobacco Control, Volume 14: Effectiveness of Tobacco Tax and Price Policies for Tobacco Control*. Lyon, France.
Ipsos. 2018a. 2018 National Tobacco Market Survey. https://web.archive.org/web/20181016150805/http://www.tobaccosa.co.za/wp-content/uploads/IPSOS-2018-National-Tobacco-Market-Study-Executive-Summary-1.pdf. [2018, Oct 16].
Ipsos. 2018b. Research Report September. https://web.archive.org/web/20190311091719/http:/www.tobaccosa.co.za/wp-content/uploads/Ipsos-Tobacco-Market-Study-REPORT.pdf. [2019, May 2].
Jenkins, S.P. 18 July 2005. Survival analysis. Unpublished manuscript, Institute for Social and Economic Research: University of Essex. https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.176.7572&rep=rep1&type=pdf. [2022, May 13].
Jha, P. & Chaloupka, F.J. 1999. *Curbing the epidemic: Governments and the economics of tobacco control.* The World BankDOI:10.1596/0-8213-4519-2.
Jorratt M. 2012. Estimación de la evasión tributaria en los impuestos selectivos al consumo: El caso de Chile. *Rev Adm Tribut.* 34:33-45.
Kahn, T. 26 May 2018. Tobacco excise revenue plunge shows SARS collection up in smoke. Business Day. https://web.archive.org/save/https://www.businesslive.co.za/bd/national/2018-05-29-tobacco-excise-revenue-plunge-shows-sars-collection-up-in-smoke/. [2019, May 2].
Kaplan, E.L. & Meier, P. 1958. Nonparametric Estimation from Incomplete Observations. *Journal of the American Statistical Association.* 53(282):457-481. DOI:10.2307/2281868.
Kay, R. & Kinnersley, N. 2002. On the Use of the Accelerated Failure Time Model as an Alternative to the Proportional Hazards Model in the Treatment of Time to Event Data: A Case Study in Influenza. *Drug Information Journal.* 36(3):571-579. DOI:10.1177/009286150203600312.
Kenkel, D., Lillard, D.R. & Liu, F. 2009. An analysis of life-course smoking behavior in China. *Health Economics.* 18 Suppl 2:S147-156. DOI:10.1002/hec.1507.
Kidd, M.P. & Hopkins, S. 2004. The Hazards of Starting and Quitting Smoking: Some Australian Evidence. *Economic Record.* 80(249):177-192. DOI:10.1111/j.1475-4932.2004.00171.x.
Kostova, D. 2013. A (nearly) global look at the dynamics of youth smoking initiation and cessation: the role of cigarette prices. *Applied Economics.* 45(28):3943-3951. DOI:10.1080/00036846.2012.736947.
Kostova, D., Chaloupka, F.J. & Shang, C. 2015. A duration analysis of the role of cigarette prices on smoking initiation and cessation in developing countries. *European Journal of Health Economics.* 16(3):279-288. DOI:10.1007/s10198-014-0573-9.
Kostova, D., Husain, M.J. & Chaloupka, F.J. 2017. Effect of cigarette prices on smoking initiation and cessation in China: a duration analysis. *Tobacco Control.* 26(5):569. DOI:10.1136/tobaccocontrol-2016-053338.
Kotnowski, K., Fong, G.T., Gallopel-Morvan, K., Islam, T. & Hammond, D. 2016. The Impact of Cigarette Packaging Design Among Young Females in Canada: Findings From a Discrete Choice Experiment. *Nicotine & Tobacco Research.* 18(5):1348-1356. DOI:10.1093/ntr/ntv114.
Lancaster, K. 1966. A New Approach to Consumer Theory. *Journal of Political Economy.* 74:132–157. DOI:10.1007/978-3-642-51565-1_34.

Lancaster, T., Hajek, P., Stead, L.F., West, R. & Jarvis, M.J. 2006. Prevention of Relapse After Quitting Smoking: A Systematic Review of Trials. *JAMA Internal Medicine.* 166(8):828-835. DOI:10.1001/archinte.166.8.828.

Laxminarayan, R. & Deolalikar, A. 2004. Tobacco initiation, cessation, and change: evidence from Vietnam. *Health Econ.* 13(12):1191-1201. DOI:10.1002/hec.932.

Leibbrandt, M., Woolard, I. & De Villiers, L. 2009. National Income Dynamic Study. Methodology: Report on NIDS Wave 1. Technical Paper no. 1. http://www.nids.uct.ac.za/publications/technical-papers/108-nids-technical-paper-no1/file. [2018, Oct 16].

Lemboe, C. & Black, P. 2012. Cigarettes taxes and smuggling in South Africa: Causes and Consequences. Working Papers 09/2012, Stellenbosch University, Department of Economics. https://ideas.repec.org/p/sza/wpaper/wpapers161.html. [2022, May 13].

Linegar, D. & Van Walbeek, C. 2018. The effect of excise tax increases on cigarette prices in South Africa. *Tobacco Control.* 27(1):65. DOI:10.1136/tobaccocontrol-2016-053340.

Little, M. & van Walbeek, C. 2018. Restaurant smoking sections in South Africa and the perceived impact of the proposed smoke-free laws: Evidence from a nationally representative survey. *South African Medical Journal.* 108(3). DOI:10.7196/SAMJ.2018.v108i3.12683.

López Nicolás, A. 2002. How important are tobacco prices in the propensity to start and quit smoking? An analysis of smoking histories from the Spanish National Health Survey. *Health Economics.* 11(6):521-535. DOI:10.1002/hec.745.

Lund, I. & Scheffels, J. 2018. Adolescent perceptions of dissuasive sticks: a web survey among 16–20 year olds in Norway. *BMC Public Health.* 18(1):974. DOI:10.1186/s12889-018-5847-1.

Madden, D. 2007. Tobacco taxes and starting and quitting smoking: does the effect differ by education? *Applied Economics.* 39(5):613-627. DOI:10.1080/00036840500447898.

Maldonado, N., Llorente, B.A., Iglesias, R.M. & Escobar, D. 2018. Measuring illicit cigarette trade in Colombia. *Tobacco Control.* 10.1136/tobaccocontrol-2017-053980. DOI:10.1136/tobaccocontrol-2017-053980.

Marti, J. 2010. Successful smoking cessation and duration of abstinence--an analysis of socioeconomic determinants. *International journal of environmental research and public health.* 7(7):2789-2799. DOI:10.3390/ijerph7072789.

Marti, J. 2014. The impact of tobacco control expenditures on smoking initation and cessation. *Health Economics.* 23(12):1397-1410. DOI:10.1002/hec.2993.

Mathe, T. 22 August 2020. Sars plan for illicit tobacco still being refined. Mail & Guardian. https://web.archive.org/web/20220504103753/https://mg.co.za/business/2020-08-22-sars-plan-for-illicit-tobacco-still-being-refined/. [2022, May 13].

McFadden, D. 1974. Conditional Logit Analysis of Qualitative Choice Behavior. In *Frontiers in Econometrics.* P. Zarembka, Ed. New York: Academic Press. 105-142.

McNeill, A., Gravely, S., Hitchman, S.C., Bauld, L., Hammond, D. & Hartmann-Boyce, J. 2017. Tobacco packaging design for reducing tobacco use. *Cochrane Database of Systematic Reviews.* 10.1002/14651858.CD011244.pub2(4). DOI:10.1002/14651858.CD011244.pub2.

Merriman, D. 2002. Understand, Measure, and Combat Tobacco Smuggling. World Bank Econmics of Tobacco Toolkit. http://siteresources.worldbank.org/INTPH/Resources/7Smuggling.pdf. [2020, Jan 29].

Mitchell, D., Critchlow, N., Moodie, C. & Bauld, L. 2021. Reactions to, and trial intentions for, three dissuasive cigarette designs: a cross-sectional survey of adolescents in Scotland. *Tobacco Control.* 30(6):623. DOI:10.1136/tobaccocontrol-2020-055842.

Monchuk, D.C., Rousu, M.C., Shogren, J.F., Nonnemaker, J. & Kosa, K.M. 2007. Decomposing the value of cigarettes using experimental auctions. *Nicotine Tob Res.* 9(1):93-99. DOI:10.1080/14622200601078392.

Moodie, C., O'Donnell, R., Fleming, J., Purves, R., McKell, J. & Dobbie, F. 2020. Extending health messaging to the consumption experience: a focus group study exploring smokers' perceptions of health warnings on cigarettes. *Addiction Research & Theory.* 28(4):328-334. DOI:10.1080/16066359.2019.1653861.

Moodie C, Stead M, Bauld L, McNeill A, Angus K, Hinds K, Kwan I, Thomas J et al. 2012. *Plain tobacco packaging: a systematic review. London: Public Health Research Consortium.*

Nargis, N., Zheng, R., Xu, S.S., Fong, G.T., Feng, G., Jiang, Y., Wang, Y. & Hu, X. 2019. Cigarette Affordability in China, 2006⁻2015: Findings from International Tobacco Control China Surveys. *International journal of environmental research and public health.* 16(7). DOI:10.3390/ijerph16071205.

Nguyen, M.T., Denniston, R., Nguyen, H.T., Hoang, T.A., Ross, H. & So, A.D. 2014. The empirical analysis of cigarette tax avoidance and illicit trade in Vietnam, 1998-2010. *PLoS One.* 9(1):e87272. DOI:10.1371/journal.pone.0087272.

Organisation for Economic Co-operation and Development. 2018. Health Statistics 2018: Definitions, Sources and Methods. Tobacco consumption in grams per capita (age 15+). http://stats.oecd.org/wbos/fileview2.aspx?IDFile=8e59b835-8196-426e-9297-15bc1dab652c. [2019, Oct 15].

Orzechowski and Walker. 2014. The Tax Burden on Tobacco. Historical Compliation. Volume 49. https://www.taxadmin.org/assets/docs/Tobacco/papers/tax_burden_2014.pdf. [2020, Jan 21].

Paraje, G. 2018. Illicit Cigarette Trade in Five South American Countries: A Gap Analysis for Argentina, Brazil, Chile, Colombia and Peru. *Nicotine & Tobacco Research.* 10.1093/ntr/nty098. DOI:10.1093/ntr/nty098.

Parliamentary Monitoring Group. 20 November 2019. ATC191121: Report of the Standing Committee on Finance on the Rates and Monetary Amounts and Amendment of Revenue Laws Bill [B17 – 2019] (National Assembly - section 77). https://web.archive.org/web/20200211103631/https://pmg.org.za/tabled-committee-report/4010/. [2020, Feb 11].

Payne, J.W., Bettman, J.R. & Johnson, E.J. 1993. *The Adaptive Decision Maker.* Cambridge, MA: Cambridge University Press.

Peretti-Watel, P. 2004. Pricing policy and some other predictors of smoking behaviours: an analysis of French retrospective data. *International Journal of Drug Policy.* 16(1):19-26. DOI:10.1016/j.drugpo.2004.06.003.

Pérez-Stable, E.J., Marín, B.V., Marín, G., Brody, D.J. & Benowitz, N.L. 1990. Apparent underreporting of cigarette consumption among Mexican American smokers. *American Journal of Public Health.* 80(9):1057-1061.

Personal communication with André Szklo. 8 May 2020. *Email reference: Under-reporting estimates in Brazil gap analysis.*

Physicians for a Smoke-Free Canada. 2013. *The Canadian Tobacco Market Place. Estimating the volume of contraband sales of tobacco in Canada: 2006–2011*. Updated and Revised—April 2011. Ottawa.

Ramos, A. & Curti, D. 2006. Economía del Control del Tabaco en los Países del Mercosur y Estados Asociados: Uruguay. Washington, DC: Organizacion Panamericana de la Salud.

Regmi, K., Kaphle, D., Timilsina, S. & Tuha, N.A.A. 2018. Application of Discrete-Choice Experiment Methods in Tobacco Control: A Systematic Review. *PharmacoEconomics - Open.* 2(1):5-17. DOI:10.1007/s41669-017-0025-4.
Republic of South Africa. 5 January 1994. No. 194 of 1993: Trade Marks Act. No. 15400. https://iponline.cipc.co.za/Publications/Acts/Trade_Marks.pdf. [2019, Feb 20].
Republic of South Africa. 18 February 2004. National Treasury. Budget Speech. http://www.treasury.gov.za/documents/national%20budget/2004/speech/Speech.pdf. [2018, Sept 1].
Republic of South Africa. 23 February 2022. National Treasury. Budget 2022 Speech. http://www.treasury.gov.za/documents/national%20budget/2022/speech/speech.pdf.
Republic of South Africa. 1995. Regulations relating to the labelling, advertising and sale of tobacco products as published in GN 2063 in GG 16111 of 2 December 1994 as amended by GN R1148 in GG 16588 of 4 August 1995. https://www.tobaccocontrollaws.org/legislation/country/south-africa/laws. [2018, Oct 20].
Republic of South Africa. 1999. Tobacco Products Control Amendment Act 1999 (Amends Act 83 of 1993). Act No. 12, 1999. Volume 406. No. 19962. https://www.gov.za/documents/tobacco-products-control-amendment-act-0. [2017, Nov 7].
Republic of South Africa. 2007. Tobacco Products Control Amendment Act 23 of 2007. https://www.gov.za/documents/tobacco-products-control-amendment-act. [2022, May 13].
Republic of South Africa. 2008. Tobacco Products Control Amendment Act 63 of 2008. https://www.gov.za/documents/tobacco-products-control-amendment-act-1. [2022, May 13].
Republic of South Africa. 2009. Tobacco Products Control Amendment Act: Commencement. https://www.gov.za/documents/tobacco-products-control-amendment-act-commencement-0. [2022, May 13].
Republic of South Africa: Department of Health. 9 May 2018. Control of Tobacco Products and Electronic Delivery Systems Bill. Government Notice No. 41617. http://www.health.gov.za/index.php/2014-03-17-09-09-38/policies-and-guidelines/doc3. [2019, Mar 20].
Republic of South Africa: Department of Health. 16 May 2011. Regulation Gazette No. 9537 Vol. 551 No. 34302. Regulations relating to the standards for manufacturing of reduced ignition propensity (RIP) cigarettes. https://www.tobaccocontrollaws.org/legislation/country/south-africa/laws. [2019, May 2].
Republic of South Africa: Department of Health. 29 September 2000. Government Gazette. Vol. 423, No. 21610, Regulation Gazette, No. 6895 No. R. 974. Notice relating to the maximum permissible yield of tar, nicotine and other constituents in tobacco products. https://www.tobaccocontrollaws.org/legislation/country/south-africa/laws. [2018, Dec 1].
Republic of South Africa: Department of Trade and Industry. 2019. Trade data. http://tradestats.thedti.gov.za. [2018, May 2].
Republic of South Africa: National Treasury. National Budget. Available: https://web.archive.org/web/20181016103436/http://www.treasury.gov.za/documents/national%20budget/default.aspx [2018, Oct 16].
Roemer, R., Taylor, A. & Lariviere, J. 2005. Origins of the WHO Framework Convention on Tobacco Control. *American Journal of Public Health.* 95(6):936-938. DOI:10.2105/AJPH.2003.025908.

Ross, H. 2015. Understanding and measuring tax avoidance and evasion: A methodological guide. http://www.reep.uct.ac.za/etcp/publications/reports. [2022, May 13].
Ross, H. 2017. Tracking and tracing tobacco products in Kenya. *Prev Med.* 105:S15-S18. DOI:https://doi.org/10.1016/j.ypmed.2017.04.025.
Ross, H., Kostova, D., Stoklosa, M. & Leon, M. 2014. The impact of cigarette excise taxes on smoking cessation rates from 1994 to 2010 in Poland, Russia, and Ukraine. *Nicotine & Tobacco Research.* 16 Suppl 1:S37-43. DOI:10.1093/ntr/ntt024.
Ross, H., Vellios, N., Batmunkh, T., Enkhtsogt, M. & Rossouw, L. 2019. The impact of tax increases on illicit cigarette trade in Mongolia. *Tobacco Control.* 10.1136/tobaccocontrol-2018-054904. DOI:10.1136/tobaccocontrol-2018-054904.
Roth, M.A., Aitsi-Selmi, A., Wardle, H. & Mindell, J. 2009. Under-reporting of tobacco use among Bangladeshi women in England. *Journal of Public Health.* 31(3):326-334. DOI:10.1093/pubmed/fdp060.
Rousu, M.C. & Thrasher, J.F. 2013. Demand Reduction from Plain and Pictorial Cigarette Warning Labels: Evidence from Experimental Auctions. *Applied Economic Perspectives and Policy.* 35(1):171-184. DOI:10.1093/aepp/pps049.
Rousu, M.C., Marette, S., Thrasher, J.F. & Lusk, J.L. 2014. The economic value to smokers of graphic warning labels on cigarettes: Evidence from combining market and experimental auction data. *Journal of Economic Behavior & Organization.* 108:123-134. DOI:10.1016/j.jebo.2014.09.003.
Ryan, M., Gerard, K. & Amaya-Amaya, M. 2008. *Using Discrete Choice Experiments to Value Health and Health Care.* SpringerDOI:10.1007/978-1-4020-5753-3.
Select Committees on Finance. 4 November 2019. Rates and Monetary Amounts and Amendment of Revenue Laws Bill [B17-2019] (Rates Bill), Taxation Laws Amendment Bill [B18-2019] (TLAB),& Tax Administration Laws Amendment Bill [B19-2019] (TALAB). https://web.archive.org/web/20200211111836/https://pmg.org.za/call-for-comment/869/. [2020, Feb 11].
Senkubuge, F. 2020. Smoking-related health risk knowledge, and reactions to cigarette warning labels amongst South African adults. PhD thesis: University of Pretoria. https://repository.up.ac.za/handle/2263/77240. [2022, May 14].
Singer, J.D. & Willett, J.B. 1993. It's About Time: Using Discrete-Time Survival Analysis to Study Duration and the Timing of Events. *Journal of Educational Statistics.* 18(2):155-195. DOI:10.3102/10769986018002155.
Singer, J.D. & Willett, J.B. 2003. *Applied Longitudinal Data Analysis: Modeling Change and Event Occurrence.* New York: Oxford University Press.
Smith, K.E., Savell, E. & Gilmore, A.B. 2013. What is known about tobacco industry efforts to influence tobacco tax? A systematic review of empirical studies. *Tobacco Control.* 22(2):144-153. DOI:10.1136/tobaccocontrol-2011-050098.
Sole, S. 28 October 2018. Smokes, sex and the arms deal. Mail & Guardian. https://web.archive.org/save/https://mg.co.za/article/2008-10-28-smokes-sex-and-the. [2019, May 2].
South Africa Market Audience Foundation. The Evolution of AMPS. www.saarf.co.za/amps/amps-evolution.asp. [2017, Oct 20].
South Africa Market Audience Foundation. 2011. All Media Product Survey: Special notes. http://www.saarf.co.za/amps-technicalreport/technicalreport-Jan%202011%20-%20Dec%202011/data%20files/Technical/06%20-%20Tech%202011B%20~%20Pages%2007-13.pdf. [2017, Oct 20](11 Dec 2019).
South African Audience Research Foundation. 1995. *All Media and Product Survey [dataset]*. Cape Town: Version 1. Johannesburg: South African Audience Research Foundation [producer]. Cape Town: DataFirst [distributor], 2012.

South African Audience Research Foundation. 2002. *All Media and Products Survey [dataset]*. Version 1.1. Johannesburg: South African Audience Research Foundation [producer]. Cape Town: DataFirst [distributor], 2015.
South African Audience Research Foundation. 2011. *All Media and Products Survey [dataset]*. Version 1.1. Johannesburg: South African Audience Research Foundation [producer]. Cape Town: DataFirst [distributor], 2015.
South African Audience Research Foundation. 2014. *All Media and Products Survey*. Version 1.1. Johannesburg: South African Audience Research Foundation [producer]. Cape Town: DataFirst [distributor], 2017.
South African Audience Research Foundation. 2015. *All Media and Products Survey*. Version 1.1. Johannesburg: South African Audience Research Foundation [producer]. Cape Town: DataFirst [distributor], 2019.
South African Reserve Bank. 2022. Statistical tables: Money and banking. www.resbank.co.za/content/dam/sarb/publications/quarterly-bulletins/quarterly-bulletin-publications/2022/march/11Statistical%20tables%20National%20accounts.pdf. [2022, Apr 1].
South African Revenue Service. 8 December 2021. Oakbay director sentenced to 10 years direct imprisonment. https://www.sars.gov.za/media-release/oakbay-director-sentenced-to-10-years-direct-imprisonment/. [2022, May 13].
South African Revenue Service. 19 August 2014. Portfolio Committee on Trade & Industry. https://web.archive.org/web/20181008144419/https://www.thedti.gov.za/parliament/2014/SARS_Presentation.pdf. [2018, Sep 15].
South African Revenue Service. 24 August 2018. SARS to re-establish the Large Business Unit and Illicit Economy Team. https://web.archive.org/web/20220504081330/https://www.sars.gov.za/media-release/24-august-2018-sars-to-re-establish-the-large-business-unit-and-illicit-economy-team/.
South African Revenue Service. 2012. Compliance Programme 2012/13 − 2016/17. https://www.sars.gov.za/wp-content/uploads/Enterprise/Strat/SARS-Strat-07-G02-Compliance-Programme-2012-2013-to-2016-2017—-External-Guide.pdf.
Southern Africa Labour and Development Research Unit. *National Income Dynamics Study 2017, Wave 5 [dataset]*. Version 1.0.0 Pretoria: Department of Planning, Monitoring, and Evaluation [funding agency]. Cape Town: Southern Africa Labour and Development Research Unit [implementer], 2018. Cape Town: DataFirst [distributor], 2018. DOI: 10.25828/fw3h-v708.
Southern Africa Labour and Development Research Unit. *National Income Dynamics Study (NIDS) Wave 1, 2008 [dataset]*. Version 6.1. Pretoria: SA Presidency [funding agency]. Cape Town: Southern Africa Labour and Development Research Unit [implementer], 2018. Cape Town: DataFirst [distributor], 2018. DOI:10.25828/e7w9-m033.
Spence, C. 2016. Multisensory packaging design. In *Integrating the Packaging and Product Experience in Food and Beverages*. B. P, Ed. London, UK: Elsevier. 1–22.
Spiess, A.-N. & Neumeyer, N. 2010. An evaluation of R2 as an inadequate measure for nonlinear models in pharmacological and biochemical research: a Monte Carlo approach. *BMC pharmacology*. 10:6-6. DOI:10.1186/1471-2210-10-6.
Stata Netcourse 631. 2019. Introduction to Survival Analysis Using Stata. https://www.stata.com/netcourse/intro-survival-analysis-nc631/. [2022, May 13].
StataCorp. Stata manual for streg parametric survival models. https://www.stata.com/manuals/ststreg.pdf. [2022, May 13].

StataCorp. Stata manual for stcox postestimation: posttestimation tools for stcox. https://www.stata.com/manuals/ststcoxpostestimation.pdf. [2022, May 13].
Statalist: The Stata Forum. 21 October 2018. svy total format. https://www.statalist.org/forums/forum/general-stata-discussion/general/1466779-svy-total-format. [2020, Feb 24].
Statistics South Africa. 2017. Mid-year population estimates 2017. http://www.statssa.gov.za/publications/P0302/P03022017.pdf [2018, Jun 20].
Stehr, M. 2005. Cigarette tax avoidance and evasion. *J Health Econ.* 24(2):277-297. DOI:10.1016/j.jhealeco.2004.08.005.
Stensrud, M.J. & Hernán, M.A. 2020. Why Test for Proportional Hazards? *JAMA.* 323(14):1401-1402. DOI:10.1001/jama.2020.1267.
Szklo, A., Iglesias, R.M., Carvalho de Souza, M., Szklo, M. & Maria de Almeida, L. 2018. Trends in Illicit Cigarette Use in Brazil Estimated From Legal Sales, 2012-2016. *American Journal of Public Health.* 108(2):265-269. DOI:10.2105/ajph.2017.304117.
Tauras, J. 1999. The Transition to Smoking Cessation: Evidence from Multiple Failure Duration Analysis. *National Bureau of Economic Research.* Working Paper No. 7412.
Tauras, J. & Chaloupka, F. 1999. Determinants of smoking cessation: An analysis of young adult men and women. *National Bureau of Economic Research.* Working paper 7262.
Tauras, J., O'Malley, P. & Johnston, L. 2001. Effects of price and access laws on teenage smoking initiation: a national longitudinal analysis. NBER Working paper no. 8331. *National Bureau of Economic Research.* Working paper no. 8331.
Thrasher, J.F., Rousu, M.C., Hammond, D., Navarro, A. & Corrigan, J.R. 2011. Estimating the impact of pictorial health warnings and "plain" cigarette packaging: evidence from experimental auctions among adult smokers in the United States. *Health Policy.* 102(1):41-48. DOI:10.1016/j.healthpol.2011.06.003.
Thrasher, J.F., Islam, F., Arillo-Santillán, E., Rodriguez-Bolaños, R., Saenz de Miera Juarez, B., Hardin, J.W. & Barrientos-Gutierrez, I. 2022. Strategies to enhance the effects of pictorial warnings for cigarettes: results from a discrete choice experiment. *Addiction.* 117(4):1095-1104. DOI:10.1111/add.15725.
Tobacco Institute of South Africa. 5 November 2019. Submission on the medium term budget policy statement. Revised Fiscal framework and revenue proposals
Tobacco Institute of South Africa. 2019. https://web.archive.org/save/https://www.tobaccosa.co.za/. [2020, Jan 20].
Tobacco Institute of Southern Africa. 2016. How serious is illicit trade. https://web.archive.org/web/20180906131224/http://www.tobaccosa.co.za/illicit-trade/how-serious-is-illicit-trade/. [2018, Oct 12].
U.S. National Cancer Institute and World Health Organization. 2016. *The Economics of Tobacco and Tobacco Control*. National Cancer Institute Tobacco Control Monograph 21. NIH Publication No. 16-CA-8029A. Bethesda, MD: U.S. Department of Health and Human Services, National Institutes of Health, National Cancer Institute; and Geneva, CH: World Health Organization.
UK Parliament. 14 June 2021. Bill 287 2021-22. Cigarette Stick Health Warnings Bill [HL] Private Members' Bill (Starting in the House of Lords). Session 2021-22. https://bills.parliament.uk/bills/2889 [2022, May 13].
United Nations Department of Economic and Social Affairs. Population Division. World Population Prospects 2017. https://population.un.org/wpp/Download/Standard/Population/. [2018, Oct 10].
United Nations Treaty Collection. 2022a. Protocol to Eliminate Illicit Trade in Tobacco Products. Status as at 07-04-2022. https://treaties.un.org/pages/ViewDetails.aspx?src=TREATY&mtdsg_no=IX-4-a&chapter=9&clang=_en. [2022, May 13].

United Nations Treaty Collection. 2022b. WHO Framework Convention on Tobacco Control. Status as at 07-04-2022. https://treaties.un.org/pages/ViewDetails.aspx?src=TREATY&mtdsg_no=IX-4&chapter=9&clang=_en. [2022, Jan 5](2022, Jan 5).
Van der Zee, K., Van Walbeek, C. & Magadla, S. 2019. Illicit/cheap cigarettes in South Africa. *Trends in Organized Crime.* 10.1007/s12117-019-09372-9. DOI:10.1007/s12117-019-09372-9.
Van der Zee, K., Filby, S. & Van Walbeek, C. 2022. When Cigarette Sales Suddenly Become Illegal: Evidence From an Online Survey of South African Smokers During COVID-19 Lockdown. *Nicotine & Tobacco Research.* 10.1093/ntr/ntac067:ntac067. DOI:10.1093/ntr/ntac067.
Van der Zee, K., Vellios, N., Van Walbeek, C. & Ross, H. 2020. The illicit cigarette market in six South African townships. *Tobacco Control.* 10.1136/tobaccocontrol-2019-055136. DOI:10.1136/tobaccocontrol-2019-055136.
Van Dyk, J. 7 September 2018. Did Big Tobacco buy Twitter? Bhekisisa: Centre for Health Jounalism. https://web.archive.org/save/https://bhekisisa.org/article/2018-09-07-00-did-big-tobacco-buy-twitter-industry-fights-new-tobacco-control-bill/. [2020, Jan 20].
Van Loggerenberg, J. 2019. *Tobacco Wars.* Cape Town: South Africa: Tafelberg: NB Publishers.
Van Rensburg, D. 8 July 2018. The rot runs deep in the tobacco sector. fin24. https://web.archive.org/save/https://www.fin24.com/Economy/South-Africa/the-rot-runs-deep-in-the-tobacco-sector-20180708-2 [2018, Oct 15].
Van Walbeek, C. 2005. The Economics of Tobacco Contol in South Africa. PhD dissertation. University of Cape Town.
Van Walbeek, C. 2014. Measuring changes in the illicit cigarette market using government revenue data: the example of South Africa. *Tobacco Control.* 23(e1):e69. DOI:10.1136/tobaccocontrol-2013-051178.
Van Walbeek, C. 2018. *South Africa time series data for cigarettes: 1960−2017. [dataset].* Version1.0. Cape Town: Economics of Tobacco Control Project [producer], 2018. Cape Town: DataFirst [distributor], 2018.
Van Walbeek, C. & Filby, S. 20 September 2021. Up in smoke: Batsa's cigarette pricing strategy has backfired, exposing its greedy, grubby underbelly. Daily Maverick. https://www.dailymaverick.co.za/article/2021-09-20-up-in-smoke-batsas-cigarette-pricing-strategy-has-backfired-exposing-its-greedy-grubby-underbelly/.
Van Walbeek, C., Van der Zee, K. & Filby, S. 10 December 2020. Back to Normal? Smoking and quitting behaviour in South Arica after the tobacco sales ban: Results from a third survey. http://www.reep.uct.ac.za/news/smoking-and-quitting-behaviour-south-africa-after-tobacco-sales-ban-results-third-survey. [2022, May 13].
Van Walbeek C, Van der Zee K & Vellios N. 5 March 2020. Trade in illicit cigarettes on the way to being stubbed out. Daily Maverick. https://web.archive.org/web/20220504083616/https://www.dailymaverick.co.za/article/2020-03-05-trade-in-illicit-cigarettes-on-the-way-to-being-stubbed-out/.
Vellios, N. & Van Walbeek, C. 2016. Determinants of regular smoking onset in South Africa using duration analysis. *BMJ Open.* 6(7). DOI:10.1136/bmjopen-2016-011076.
Vellios, N. & van der Zee, K. 2020. Dataset on cigarette smokers in six South African townships. *Data in Brief.* 32:106260. DOI:10.1016/j.dib.2020.106260.
Vellios, N., Ross, H. & van Walbeek, C. 2019. The illicit trade of cigarettes in South Africa: 2002−2017. *Tobacco Control.* 10.1136/tobaccocontrol-2018-054798. DOI:10.1136/tobaccocontrol-2018-054798.
Vojáček, O. & Pecáková, I. 2010. Comparison of discrete choice models for economic environmental research. *Prague Economic Papers.* 1:35-53. DOI:10.18267/j.pep.363.

Warner, K.E. 1978. Possible Increases in the Underreporting of Cigarette Consumption. *Journal of the American Statistical Association.* 73(362):314-318. DOI:10.1080/01621459.1978.10481575.
Wooldridge, J.M. 2013. *Introductory Econometrics: A Modern Approach.* 5th edition. USA: South-Western, Cengage Learning.
World Bank. 2019. Confronting Illicit Tobacco Trade: a Global Review of Country Experiences. *WBG Global Tobacco Control Program.* http://documents.worldbank.org/curated/en/677451548260528135/Confronting-Illicit-Tobacco-Trade-a-Global-Review-of-Country-Experiences.
World Health Organization. 2003. Framework Convention on Tobacco Control. https://www.who.int/fctc/text_download/en/. [2022, Jan 5].
World Health Organization. 2008a. Guidelines for implementation of Article 11 of the WHO Framework Convention on Tobacco Control (Packaging and labelling of tobacco products) (decision FCTC/COP3(10)). https://www.who.int/fctc/guidelines/article_11.pdf. [2022, May 13](2022, Jan 5).
World Health Organization. 2008b. Guidelines for implementation of Article 13 of the WHO Framework Convention on Tobacco Control (Tobacco advertising, promotion and sponsorship) (decision FCTC/COP3(12)). https://www.who.int/fctc/guidelines/adopted/article_13/en/. [2022, May 13].
World Health Organization. 2010. WHO Technical Manual on Tobacco Tax Administration. https://www.who.int/tobacco/publications/tax_administration/en/. [2018, Oct 18].
World Health Organization. 2013. Framework Convention on Tobacco Control. Protocol to Eliminate Illicit Trade in Tobacco Products. http://www.who.int/fctc/protocol/illicit_trade/protocol-publication/en/. [2018, Sep 2].
World Health Organization. 2014. Guidelines for the implementation of Article 6 of the WHO FCTC (Decision FCTC/COP6(5)). https://www.who.int/fctc/guidelines/adopted/Guidelines_article_6.pdf. [2022, Jan 5].
World Health Organization. 2021a. WHO report on the global tobacco epidemic 2021. Web Annex VI: Global Tobaccol Control Policy Data. 9.1 Taxes and retail price for a pack of 20 cigarettes most sold brand. https://www.who.int/publications/i/item/WHO-HEP-HPR-TFI-2021.9.1. [2022, May 13].
World Health Organization. 2021b. WHO Technical Manual on Tobacco Tax Administration. https://www.who.int/publications/i/item/9789240019188. [2022, May 13].
World Health Organization. 2022. Guidelines and policy options and recommendations for implementation of the WHO FCTC. https://www.who.int/fctc/guidelines/en/. [2022, Jan 5].
World Trade Organization. 9 June 2020. Australia – certain measures concerning trademarks, geographical indications and other plain packaging requirements applicable to tobacco products and packaging. https://www.wto.org/english/tratop_e/dispu_e/435_441abr_conc_e.pdf. [2022, Jan 5].