Assessing Demand for Green Electricity Products amongst upper-middle income Western Cape Households: A Contingent Valuation Study.

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Abstract

The study presented in this paper examines the demand for green electricity products amongst upper-middle income Western Cape households. A social cost-benefit analysis to inform electricity investment planning requires the environmental benefit of using green electricity to be expressed in monetary terms. Since existing markets trade in electricity as a homogenous good, market data is of little use in this regard, and non-market valuation approaches are required.

This study seeks to answer three key questions: To what extent would upper-middle income households in the Western Cape Province be willing to purchase premium-priced green electricity products? What is the maximum amount that a typical upper-middle income Western Cape household would be willing to pay for such a green electricity product? And: What are the demographic and attitudinal characteristics of adopting households and their members? To answer these questions the contingent valuation methodology was employed, using primary data from a survey (n=464) conducted in Cape Town during April and May of 2012. This survey sought to assess WTP using a hypothetical market, and gathered data on eleven demographic and attitudinal factors selected as possible determinants of WTP on the basis of a literature review.

The survey instrument presented a hypothetical market trading in a fictional range of green electricity products named *Green Power!©, Green Power!© Plus,* and *Green Power!© Lite.* This hypothetical market used a double-bounded dichotomous choice item with a range of bid values (R50 to R300/month) to elicit respondent WTP for these products. A number of approaches were taken in econometric analysis of the response data. Estimates of WTP were produced using non-parametric survival-time models, single-bounded logit and probit models, and double-bounded bivariate probit and interval-data models. After each dichotomous choice item, respondents were asked how confident they were of their answer. This data was used to calibrate the dichotomous choice responses for some models, recoding 'yes' responses with reported confidence below a chosen threshold value as 'no' responses.

In all, nearly 80% of respondents indicated that they would sign up for one or more of the green electricity products presented to them, though the confidence reported in these commitments varies widely. Only 42% of the sample reported confidence of 70% or more in their agreement to purchase, which indicates that many respondents do not consider their own responses in the hypothetical market to be sincere. Though the inclusion of a follow-up item assessing confidence in the responses given to dichotomous-choice questions is not common practice, the results obtained by this study strongly recommend the use of such an item.

The valuation results from this study are presented as a range of possible values. The lower bound of this range is defined by the results from a highly conservative non-parametric model and response data calibrated at a 70% certainty threshold. This model found a mean WTP of R67.65 per household per month. This is equivalent to around 9% of a typical upper-middle income household's electricity spending, and corresponds to an aggregate WTP of R31.2 million rand per month. The upper bound of the range is defined by the results of the very popular double-bounded interval-data model of Hanemann *et al*. (1991). This model finds mean WTP of R227.13 per household per month. This is equivalent to a premium of around 30% of existing electricity spending, and corresponds to an aggregate WTP of slightly less than R105 million per month. The mean WTP of upper-middle income Western Cape households is thus found to lie in the range of R68 000 000 – R227 000 000 per month.

Characteristics found to be statistically significant positive predictors of WTP for green electricity include: household income; awareness of and concern related to anthropogenic climate change; positive perceptions of renewable energy technologies as sources of electricity; and solar geyser ownership. Factors found to be statistically significant negative predictors of WTP for green electricity include; respondent age, education, and positive perceptions of nuclear energy.

The study concludes with recommendations for marketing of green electricity products and the conduct of similar contingent valuation research, as well as an analysis of the trends observed in the emerging South African green electricity valuation literature.

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Assessing the demand for green electricity products amongst Western Cape households: A Contingent Valuation Study

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Chapter One: Introduction

Introduction: Electricity and Green Electricity in South Africa

There is a growing consensus in the scientific community that the current pattern of human development based on cheap energy from fossil fuels poses unacceptable long run risks to the ecology and climate of the planet. In its fourth Assessment Report, published in 2007, the Intergovernmental Panel on Climate Change (IPCC) reiterated the strength of the evidence for a causal link between anthropogenic emissions of greenhouse gasses and the climatic changes observed over the past few decades, and outlined the potentially catastrophic consequences of inaction. To avoid the worst outcomes, the IPCC scientists deemed it vital that average warming be kept below two degrees Celsius, which would require stabilising atmospheric greenhouse gas concentrations below 450ppm CO_2 equivalent (IPCC, 2007). Since the formation of the IPCC in 1988, and the commencement of negotiations through the United Nations Framework Convention on Climate Change, the reduction of greenhouse gas emissions has become a high profile issue around the world. Governments in many countries (including South Africa) and cities from around the world have drafted plans and begun working to reduce their greenhouse gas emissions. In 2009, as part of their commitments to the Copenhagen Accord, South Africa pledged cuts in greenhouse gas emissions of 34% by 2020, and 42% by 2025 (Department of Energy, 2010).

Producing 78% of greenhouse gas emissions, the energy sector is by far the biggest contributor to greenhouse gas emissions in South Africa. This is primarily due to the extensive use of coal fired power stations, which provide 92% of the electricity produced in South Africa (Department of Environmental Affairs, 2010). If South Africa is to honour its emissions reduction commitments to the Copenhagen Accord, this will require shift away from coal and towards low-carbon electricity sources like nuclear power and renewable energy technologies.

From 1994 to 2007, Eskom provided South Africans with electricity services that were amongst the cheapest and most reliable in the world (Eskom 2012; Department of Energy, 2010). The historically low price of electricity in South Africa is generally attributed to the absence of capital costs due to an inherited capacity surplus, as well as long term agreements securing coal supply at prices well below those on global export markets (Department of Energy, 2010; Sebitosi & Pillay, 2008). However, since 1994, the demand for electricity in South Africa has grown steadily, driven by economic growth, the rise of new a consumer class, and the extension of the grid to previously unserved areas (Winkler, 2005; Department of Energy, 2010).

This rise in demand was not met by a corresponding increase in electricity supply, and so, in late 2007 and early 2008 South Africa faced rolling blackouts, as Eskom instituted a 'load-shedding' schedule to maintain its minimum reserve margin (Department of Energy, 2010). Following the immense disruption that accompanied the load-shedding experience and facing long-term supply uncertainty, the Government of South Africa published a plan for the development of the electricity sector over the coming twenty years (Department of Energy, 2010). The Integrated Resource Plan for Electricity 2010-2030 examines the likely path of future electricity demand, and the various combinations of generation technologies that would be required to maintain adequate supply.

The scenarios considered in the Integrated Resource Plan require investment in electricity infrastructure on an unprecedented scale. The estimated present-value cost of the capacity expansion scenarios considered by the Integrated Resource Plan range from R789 000 000 000 for the 'base-case' scenario to R1250 000 000 000 for the 'Emissions Limit 3' scenario (Department of Energy, 2010). The nature of the investments made over the next twenty years will determine the shape of the future South African electricity sector, and they present an ideal opportunity for government to initiate the necessary shift towards a low-emissions electricity sector.

The investment portfolio recommended by the Integrated Resource plan is known as the 'Policy Adjusted Revised Balanced Scenario'. This plan was approved by cabinet in late 2010, and was published in the Government Gazette on May 6th 2011. In addition to the

Medupi and Kusile power stations (4.8GW each – both coal fired), this plan calls for a 9.6GW fleet of nuclear reactors, 6.3GW of new coal power, 17.8GW of renewable energy capacity, and 8.9GW from 'other sources'. This plan envisages that by 2030, annual electricity consumption in South Africa will be 454TWh. The share of electricity produced from coal will decline from over 90% to around 65%, whilst renewable energy sources will supply 9%, up from an effective 0.0% in 2010 (Department of Energy, 2010). The increased use of low-emitting nuclear and renewable energy technologies is a key component of South Africa's national emissions-reduction strategy (Department of Environmental Affairs, 2010).

The primary obstacle to the completion of this plan is cost. It is widely accepted that the unit-cost of generating electricity from renewable technologies is higher than those of new fossil fuel plants. Whilst the planned increase in the use of renewable energy technologies is certainly admirable, important questions regarding the ultimate source of funds for these investments remain as yet unanswered (Department of Energy, 2010; NERSA, 2012). The early stages of the capacity expansion plan have been financed through a program of substantial annual electricity price increases, as well as the issue of new government-guaranteed debt (NERSA, 2012).

International experience suggests that some businesses and households may be willing to bear the burden of this higher cost by voluntarily purchasing green electricity at a premium price. If electricity retailers were to introduce a range of green electricity products designed to cater to this demand, the revenues realised from the sale of such products could reduce the increases in the general price of electricity and fiscal outlay required to complete the envisaged capacity expansion.

However, very little is known about the demand for green electricity in South Africa. The retail market trades in electricity as a homogenous good, and does not differentiate by generation source. The choices presented by these markets do not offer consumers the opportunity to express their preferences for different generation sources, and the data they produce is thus of little use as a guide to consumer preferences.

There has also been very little research done on demand for green electricity in South Africa. The first known investigation of the potential green electricity market was commissioned by the City of Cape Town and conducted by A.C. Nielsen in 2002. This study sought to establish an estimate of the demand for green electricity that could be expected from consumers residing in the Western Cape. The results obtained from their survey revealed most respondents to have very limited knowledge of both environmental issues and green electricity. A full 80% of survey respondents claimed never to have heard the term 'green electricity' before. The results of this study indicated that 37% of Western Cape households surveyed would be willing to voluntarily adopt a green electricity product sold at a price premium of 23c/kWh, whilst on 24% would be willing to pay 31c/kWh.

A second study on the demand for green electricity was conducted in 2009 by a team of researchers from the University of Stellenbosch Business School. Oliver, Volschenk & Smit (2011) used a telephone-based survey of households within the Cape Peninsula to assess their willingness to purchase green electricity at premium prices. This study sought to measure the likely magnitude of green electricity demand, as well its determinants (Oliver, 2009; Oliver *et al.,* 2011). Overall, this study found 42% of Cape Peninsula households to be willing to pay an unspecified premium price for green electricity, whilst 38% declared themselves unwilling to pay any premium. Amongst willing households, the average price premium indicated was 26% of their existing electricity bill, or 15c/kWh. This premium suggests that the sale of green electricity products could yield up to R39 000 000 per month in revenue (Oliver, 2009).

Research aims

Considering their age and the multitude of changes that the electricity market has undergone in the intervening years, these studies are of questionable value as a guide for policymaking and resource planning in the present day. This study thus seeks to update and advance the understanding of green electricity demand amongst Western Cape households in a few key ways.

First, whilst the study by Oliver *et al.,* (2011) was published recently, the South African electricity market has undergone many changes since late-2007/early-2008, when their data was gathered. The most notable of these changes is the rise in retail electricity prices from around 60c/kWh to R1.06/kWh over the intervening period. Re-examining the demand for green electricity will thus facilitate an examination of the changes in WTP for green electricity produced by a sharp change in the price of basic electricity services. A second notable change is the end of Eskom's use of scheduled load-shedding as a means of controlling electricity demand. The survey used by Oliver *et al*. (2011) was administered during the period in which Eskom was actively engaging in load-shedding. This period saw South Africans facing unstable electricity supply, and frequent electricity outages; an experience which was unfamiliar to most suburban households. It is intuitively reasonable to expect that the responses gathered during this atypical period may provide an inflated view of WTP due to respondent anxiety regarding the security of electricity supply. This study thus follows the recommendations made by Oliver (2009) by examining WTP for green electricity during a period of stable electricity supply, and assessing the effects of general electricity price increases on WTP estimates.

Notable changes are also anticipated in the attitudes that consumers express towards electricity and the environment. Environmental awareness is anticipated to have risen, buoyed by major global events such as the COP19 conference hosted by Durban in November 2011.

Finally, by applying the contingent valuation methodology, this study seeks to undertake a more rigorous examination of WTP. Though both A.C. Nielsen (2002) and Oliver (2009) sought to evaluate WTP for green electricity using survey responses, the approach taken in these studies was more akin to market research than non-market valuation. These studies simply asked respondents about their willingness to purchase a premium-priced green electricity product. No hypothetical market was developed, and few details regarding the exact nature of the green electricity product and the arrangements for its provision were provided. By contrast, this study adopts the full contingent valuation methodology, developing a hypothetical market trading in a range of fictional green electricity products called the *Green Power!* products. These products were based on the 15% green electricity target adopted by the Western Cape Provincial Government, and were carefully designed to be as realistic as possible.

The paper is structured as follows: Chapter 2 examines the contingent valuation methodology, discussing its history, strengths, applications, and weaknesses. Chapter 3 presents a review of selected green electricity valuation literature. Chapter 4 discusses the choices made in designing the survey and the hypothetical market used for eliciting WTP data from respondents. Chapter 5 explains the various approaches taken in modelling the demand for green electricity products from the hypothetical market response data. Chapter 6 presents the response data obtained from the survey, and Chapter 7 presents the results from econometric analysis of this data. A discussion of these results and their policy implications make up Chapter 8. Chapter 9 concludes this thesis with a comparison of the results obtained in this study to those found by A.C. Nielsen (2002) and Oliver *et al.,* (2011). Comparing these results allows a loose examination of the trends observed in the emerging South African green electricity valuation literature.

Chapter Two: Investing in Renewable Energy

Cost benefit analysis, market failure, and the contingent valuation methodology

Completing the capacity expansion outlined in the Integrated Resource Plan (Department of Energy, 2010) and attaining the 15% green electricity target adopted by the Western Cape Government will both require substantial public or private investment in renewable energy. Chapter 2 begins with a discussion of the cost-benefit analysis procedure that should precede and inform investment in electricity generation capacity. Section 2.2 examines a number of key failures in the market for electricity, and the resultant shortcomings of market data as a guide to the preferences of electricity consumers. Section 2.3 introduces the notion of non-market valuation, and gives a brief guide to the approaches commonly taken when money values must be attached to goods not typically traded in markets. Section 2.4 presents the contingent valuation methodology, outlining its history, and discussing the choices that must be made regarding key elements of the methodology. Further, attention is paid to the nature and sources of the biases commonly encountered in contingent valuation studies. The chapter concludes by examining the applicability of the contingent valuation methodology in a developing-world context.

2.1: Cost benefit analysis

Cost-benefit analysis is one of the conceptual cornerstones of economic theory, and it provides a compelling and powerful method for assessing the relative merits of rival projects competing for scarce resource inputs. Typically, analysts seek to establish a measure of the overall merit, or net benefit produced by some prospective change to the status quo by computing the *Net Present Value (NPV)* of a proposed project. This measure represents the present (discounted) value of all foreseen benefits produced by a project, less the present value of the foreseen costs of implementation (Dewhurst, 1972; James 1994). Computing net present values facilitates direct comparison of the relative merits of rival projects in a simple and easily understood manner. By clarifying and simplifying choices that are often complex and confusing, cost-benefit analysis has the potential to inform and guide the decision making process. Further, by requiring that costs and trade-offs be explicitly considered, cost-benefit analysis can improve the transparency of public decision-making. This in turn leaves the makers of those decisions more accountable to the public, and should produce more efficient resource allocations (Common, 1988; Dewhurst, 1972). In the extreme, net present values for rival projects can facilitate the use of Bayes' Decision Rule, which holds that decision makers should simply ensure that analyses are complete, and then approve those projects producing the highest utility gains (Dewhurst, 1972; James 1994).

Though conceptually powerful, CBA has a number of shortcomings which complicate its application in the real world. One key problem that has troubled economists for some time now relates to the proper treatment of goods for which no obvious price exists. Whilst economic theory is unambiguous in its requirement that all costs and benefits arising from the project be included in the analysis, many of these are extremely difficult to express in monetary terms. This difficulty may arise from the markets for these goods being absent, incomplete or highly restricted, as is commonly the case for public goods, and prospective goods not yet being traded (Diaz-Rainey & Tzavara, 2009).

To make informed decisions regarding the appropriate level of investment in renewable energy technologies, a great deal of information is required regarding consumer preferences in the market for electricity.

2.2: Green Electricity and Market Failure

The main benefit of using conventional technologies based on the combustion of fossil fuels is the convenience, reliability, and cost effectiveness that they offer as a source of electricity. However, in their operation, these technologies produce a number of external costs, the most notable of which is the emission of pollutants like suspended particulate matter, CO_2 and SO_2 (IPCC, 2007). Though the adverse effects of these pollutants impose a real cost on society at large, producers are generally not required to pay these costs, and they are often left uncounted. The cost of generating electricity from a conventional coal or gas fired plant is also subject to change as the price of fuel inputs varies (Brown, 2001; Winkler, 2005).

Renewable energy technologies, by contrast, are notable for their intermittency, relatively high cost, and unpredictable performance as sources of grid-power (Department of Energy, 2010). However, generating electricity from renewable energy sources produces a number of positive externalities. Investing in renewable energy technologies is anticipated to realise present and future benefits through two effects. First, an increase in the share of electricity supplied from renewable sources should, ceteris paribus, produce a corresponding decline in the use of depletable fossil fuels and their attendant pollutant emissions. Secondly, as the demand for green electricity grows, this creates incentives for producers to engage in research and development that will further improve the renewable energy technologies themselves (Wusthagen & Bilharz, 2006; Department of Energy, 2010). Most renewable energy technologies are immature in their application to large-scale grid generation. Thus, as the industry gains experience in the production and application of a particular technology, substantial 'learning effects' are expected to result in improved performance and reduced cost (Department of Energy, 2010). These benefits do not accrue to the current market participants, and are thus not reflected in market prices. Further, since most renewable technologies require no fuel inputs (biomass is an exception), the cost of generating electricity from these technologies is likely to remain fairly stable over the life of the plant. Using renewable energy technologies thus also provides utilities with a measure of protection against increases in the price of fuel inputs.

Where electricity markets do not allow price-discrimination by generation-source, utilities have no opportunity to recoup the higher costs of generating electricity using renewable energy. Though renewable energy technologies produce additional non-use benefits, these remain external to markets that trade in electricity as a homogenous good. Further, where utilities are not obliged to pay the cost of the pollution they emit, this constitutes an effective subsidy on the use of pollution-intensive generation sources. Thus, source-indifferent electricity markets present utilities with private incentives that encourage them to invest in generation capacity fired by fossil fuels to an extent that is socially inefficient (Brown, 2001; Wiser, 2007).

Retail electricity markets are also subject to multiple failures, even where they do offer an optional premium-priced green electricity product. Given that the pollutants emitted by fossil-fuel combustion impose costs on society that are regional (SO_2 and suspended particulate matter) or global (methane, CO_2) in their scope, the benefits of reducing fossil-fuel use are distributed over correspondingly vast areas and populations. These benefits – cleaner air, healthier ecosystems, and lower CO_2 emissions – are public goods. They are essentially non-rival in consumption, and there is no plausible means by which they could be maintained as the exclusive preserve of those who purchase them (Tietenberg, 2006). Thus, the distribution of costs and benefits that individual consumers face when considering the purchase of a green-electricity product provide a textbook example of the 'free-rider' problem. The benefits of purchasing a green-electricity product are freely enjoyed by adopters and non-adopters alike, whilst the costs are borne exclusively by those who purchase the good. The optimal outcome for any single respondent is thus to enjoy the benefits provided by the purchases of others, without having to bear any of the cost themselves (Wiser, 2007; Oliver, 2009).

Thus, in the absence of some rectifying intervention, the allocations produced by the markets for both electricity and electricity-generation technologies will include excessively high levels of fossil fuels, and sub-optimally low levels of renewable energy technologies. The Integrated Resource Plan 2010-2030 outlines the national government's plan for precisely such an intervention using direct public investment through the state owned-utility, Eskom, and by creating incentives for private investment in particular projects through the Renewable Energy Feed-In Tariff (REFIT) mechanism (Department of Energy, 2010; Western Cape Provincial Government, 2010).

The theoretical prescription is clear and simple. Government should correct this market failure, either by adopting a market-based Pigouvian tax and subsidy system that realigns the private and social costs of each technology, or by directly intervening in the market using regulations or public investments to achieve the socially optimal mix of generation technologies (Common, 1977; Tietenberg, 2006). However, determining the exact nature of this intervention is likely to be a complex and contentious process. Government will be required to consider and balance a number of competing social and economic objectives in determining the optimal mix of generation technologies (Department of Energy, 2010). Investments in electricity generation plants are typically large, lumpy and long term. As such, mistakes made in this process have the potential to be tremendously costly to the country (Eskom, 2012).

However, the biggest obstacle in determining the optimal mix of generation technologies is that much of the data required to make an informed choice is presently not available. Determining the generation-mix that best suits the needs of South African electricity users requires a great deal of information about their preferences as consumers in the electricity market (Brown, 2001). However, since the retail market in South Africa trades in electricity as a homogenous good, consumers are afforded no opportunity to express their preferences for electricity generated from specific sources. Market data thus offers little in the way of sensible guidance for resource planning, or on questions related to the population's preferences for different generation technologies. Where existing markets can offer no sensible guidance regarding consumer preferences, the use of non-market approaches is required.

2.3: Non-Market Valuation

Non-market valuation techniques are the tools that economists turn to when seeking to attach a value to some good for which market data is non-existent, or otherwise unreliable as a guide to consumer preferences (Carson, 2000). Due to the immense difficulty of defining and exercising property rights over most environmental benefits, these goods are seldom traded in markets. Non-market valuation techniques thus play an important role in facilitating the inclusion of environmental goods and services in cost benefit analysis procedures (Dixon, Scura, Carpenter & Sherman, 1994).

Non-market valuation techniques can be broadly classified as either *revealed preference* or *stated preference* techniques (Garrod & Willis, 1999).

Revealed preference techniques typically seek to infer a consumer's preferences over some good by observing their behaviour in a market believed to be in some way related to the good in question. These techniques use consumer behaviour in the surrogate market as a proxy for their likely behaviour in the non-existent market for the good in question. By far the most popular revealed preference approach is the travel cost method, which uses the travel costs endured by users of a natural amenity to infer the value that visitors attach to the recreational experiences it offers (Dixon *et al.,* 1994).

By contrast, *stated preference* approaches utilise survey techniques, hypothetical markets and mock-auction procedures to elicit valuations of a particular good or service from its users/consumers. These approaches are based on the simple idea that where researchers lack information regarding consumer preferences, the best way to overcome this is to ask them. Popular stated preference approaches include contingent valuation, conjoint analysis and choice-experiment procedures (Garrod & Willis, 1999; Hanley & Spash, 1993).

2.4: The Contingent Valuation Methodology

This Section examines the contingent valuations methodology (CVM), and contains three sub-sections. The first of these is a brief description of the methodology, its applications and its history. This is followed by a discussion on the key elements of a hypothetical market, and the decisions than must be made in constructing one. Finally, the chapter concludes by assessing the problems that typically arise in contingent valuation studies.

2.4.1: What is the Contingent Valuations Methodology?

The contingent valuation methodology is a popular, though controversial technique for estimating the value of non-market goods (Arrow, Solow, Portney, Leamer, Radner & Schumann., 1993; Akai & Nomura, 2004). As a stated preference approach, contingent valuation uses survey techniques to present respondents with hypothetical market scenarios, and asks them about their preferences and behaviour as consumers in this market (Carson, 2000). Taking responses provided in the hypothetical scenario to be a reasonable proxy for likely behaviour in a corresponding real market, contingent valuation seeks to estimate a respondent's maximum willingness to pay (WTP) to ensure the provision of some desired change, or the minimum compensation that they would be willing to accept (WTA) if an undesirable change were to be realised (Carson & Hanemann, 2005; Hanley & Spash, 1993; Arrow *et al*, 1993).

If the hypothetical market can be thoughtfully constructed in a manner that respondents consider believable, then analysis of the responses it elicits can facilitate valuations for essentially any good. As such, contingent valuation is inherently more flexible as a non-market valuation technique than any revealed preference approach (Carson & Hanemann, 2005). This flexibility makes contingent valuation especially popular in the fields of environmental valuation, as it provides a powerful means for estimating the value of environmental amenities and the services that they provide. Of the widely accepted non-market valuation methods, contingent valuation alone allows for the estimation of non-use and option value components (Carson, 2000; Arrow *et al.*, 1993). These components of value, whilst somewhat abstract, have been found to be higher than use values in some cases; as such, some analysts regard the value estimates produced by other techniques as lower bound estimates for true economic value (Blighnaut & De Wit, 1999; Dixon *et al*., 1994). This flexibility is, however, offset by the substantial conceptual and practical difficulties involved in designing and administering surveys, and the numerous problems that can arise when using surveys as a guide to real behaviour (Diamond & Hausman, 1994).

Contingent valuation can provide valuable guidance to policy makers, as it allows the inclusion of externalities in cost-benefit analyses for public projects and facilitates estimation of the demand for goods where markets are absent, incomplete or tightly restricted. This includes public goods and services, and prospective goods for which markets do not yet exist (Diaz-Rainey & Tzavara, 2009).

2.4.2: History of Contingent Valuation

The first study to use the contingent valuation methodology was conducted by Davis (1963), who sought to place a monetary value on the addition of facilities to improve recreational experience provided by the woods of Maine. Thought the methodology has undergone substantial development since then, many aspects of this initial study were remarkable modern, and Davis foresaw many of the issues that were encountered by later research (Arrow *et al*., 1993; Carson & Hanemann, 2005). The popularity of the methodology grew in lockstep with the growing literature on the aspects of environmental value not readily captured by market prices. Fresh considerations of existence value by Krutilla in 1967, and option value by Weisbrod in 1964 further reinforced the notion that market prices were an inadequate measure of ecosystem values, and drove the growing field of contingent valuations research (Arrow *et al*., 2003; Carson & Hanemann, 2005). Contingent valuation was soon applied to estimate the value of pollution damages, to price environmental effects of developments and facilitate their inclusion in cost benefit analyses. Applications outside of resource valuations followed quickly, with a large body of studies seeking to evaluate healthcare, sanitation and transportation services (Carson & Hanemann, 2005).

The profile of the contingent valuation methodology was boosted considerably in the wake of the Exxon Valdez oil spill in 1989, when the National Oceanographic and Atmospheric Administration (NOAA) convened a panel of leading economists to assess the reliability of contingent valuations and their acceptability as evidence in legal proceedings (Arrow *et al.,* 1993). Considering the scale of damage cause by incidents such as the Valdez spill, the accuracy of monetary valuations attached to the environmental damages they cause is a matter of great political concern. The findings of NOAA panel, which included Nobel laureates Kenneth Arrow and Robert Solow, gave cautious support to the use of contingent valuation in valuing environmental damages. The methodology was found to be sufficiently valid that its results could be admissible in court, subject to certain restrictions/requirements (Arrow *et al,.* 1993). The 'Arrow report', as it is commonly known, was a watershed in the development of contingent valuation, and is amongst the most influential guides to best practice in the conduct of contingent valuation studies (Diamond & Hausman, 1994; Carson & Hanemann, 2005; Adaman *et al*, 2011).

2.4.3: Key Elements of a Contingent Valuation Study

Several key choices must be made in conducting a contingent valuation study. This section examines the most important decisions that a researcher must make when designing and administering a survey for use in a contingent valuation study.

Mode of survey administration

A number of possible media can be utilised in the administration of the survey, though telephone, mail, and face-to-face interviews are by far the most popular (Carson & Hanemann, 2005).

The main advantage of telephone surveys is the opportunity they provide for researchers to access geographically dispersed samples at relatively low cost. Further, conducting the survey from a centralised call-centre makes standardising the interview process easier, and facilitates interviewer monitoring. Since a large proportion (88%) of households in the Western Cape own telephones, this medium gives researchers instant access to a large proportion of the population being sampled, and is typically cheaper than other formats (Carson & Hanemann, 2005; Oliver, 2009). However, these benefits must be weighed against the shortcomings and complications of administering a contingent valuation survey over the telephone. Since the hypothetical markets introduced in a contingent valuation survey typically trade in unfamiliar goods, visual aids are often needed to describe them in sufficient detail. Further, respondents are easily bored and distracted in telephone interviews. Since participants in a telephone survey are invisible to administrators the attentiveness of respondents and sincerity of the responses they provide is difficult to assess. Finally, telephone surveys are prone to sample self-selection biases. Participating in the survey requires respondents to take some time out from their planned activities, and those individuals who agree (or refuse) to complete the interview are likely to differ systematically from the larger population being sampled. The responses obtained in telephone surveys are thus of questionable value as a guide to the preferences of the wider population (Carson & Hanemann, 2005). This format is generally troublesome for most applications, and is generally not recommended (Arrow *et al*. 1993).

A second option is to post the surveys to randomly selected members of the population being sampled. Though this low-cost, impersonal approach may again allow researchers to access larger samples of the population, the individuals who complete and return these surveys are unlikely to be a representative sample of the population. This selection bias, sometimes called 'avidity bias', is a common problem in any research that relies on respondents to actively participate in their own time without an observer present (Hanley & Spash, 1993). Moreover, the survey completion process is completely unobservable to administrators, which again introduces difficulties in assessing level of respondent understanding, or sincerity of the bids obtained (Hanley & Spash, 1993).

A final option, and that recommended by Arrow *et al.* (1993) is to administer the survey through face-to-face interviews. This is typically done using intercept-sampling in carefully chosen public areas, or by arranging to interview respondents in their homes. This approach is typically more expensive and time consuming than mail or telephone administration, and the presence of the interviewer introduces the potential for their conduct to induce a bias in responses (Hanley & Spash, 1993). This is especially the case where respondents perceive particular responses to be correct, desired, or virtuous in some way. Respondents may feel inclined to please the interviewer by misrepresenting their preferences and providing such responses. As a result, surveys administered through face-to-face interviews are especially vulnerable to social desirability bias (Abdullah, 2009). However, conducting the interview on a face-to-face basis makes the survey completion process observable, and the flexibility of this format allows administrators a chance to enquire further when respondents provide vague or unclear answers. These benefits are thought to outweigh the costs for most applications, and face-to-face survey administration is widely regarded as best-practice in contingent valuation studies (Carson & Hanemann, 2005; Arrow *et al.*, 1993).

Elicitation format

The hypothetical market component of a contingent valuation survey can use a number of possible question formats to elicit respondent valuations of the good in question. This section examines the elicitation formats most popularly used in contingent valuation, discussing their strengths and weaknesses.

The first and simplest option is an open-ended-question format, in which respondents are simply asked to state the maximum amount that they would be willing to pay in order to secure the provision of some hypothetical product or program producing the outcomes described in the hypothetical market (Carson & Hanemann, 2005). The responses gathered by an open-ended valuation item are easily interpreted, and simple to include in an econometric model. Further, open-ended items do not provide or suggest any potential WTP values to respondents, and so are immune to starting point biases. However, this format may be confusing to respondents who have no experience in trading or valuing the good in question. Since real markets seldom operate in a fashion that asks or allows consumers to specify prices, hypothetical markets using open-ended elicitation items are not realistic, and respondents may find the scenarios they present unbelievable. Finally, respondents may have an incentive to misrepresent their preferences when presented with open-ended item. This strategic bias is particularly problematic in the valuation of public goods (Carson, 2000).

A second option is to use payment cards. Here, respondents are presented with a range of suggested values, from which they are asked to choose the value that most closely approximates their WTP. The bid values presented on the card may be based on the known cost of providing the good or program, or could be derived from the expected WTP distribution (Dixon *et al*., 1994). Expectations may be derived from the results of comparable studies, or from the observed expenditures in a related market (Carson, 2000). This format may assist respondents who are unfamiliar with the good or service being valued with estimating and expressing their WTP. A major drawback to using the payment card format is that presenting multiple prices implies that the final cost of the good or program is uncertain. This is likely to diminish the realism and credibility of the exercise, and may reinforce the perception that the valuation is purely hypothetical exercise (Carson & Hanemann, 2005; Hanley & Spash, 1993).

Third, researchers could engage respondents in some form of auction process or bidding game. These games typically adopt an auction-style format, with researchers proposing ever higher (lower) bids, until the maximum (minimum) bid value is found. A particularly interesting variant on the bidding game is the convergent auction format. Here, the researcher presents the respondent with two WTP values; one so high as to be certainly rejected, and one so low as to make acceptance a near-certainty. In each subsequent round, the gap between these figures is narrowed, until, in the limit, a single acceptable bid is obtained (Dixon *et al*. 1994). This format again suffers from a lack of realism, as the credibility of the market is extremely difficult to maintain where respondents are presented with multiple prices.

Finally, the good could be presented to the respondent using a dichotomous choice, or referendum format. Here, interviewers present the hypothetical market scenario to respondents and ask them to accept or reject the good or program at the stated price (Dixon *et al*, 1994). If a respondent indicates that they would purchase the good at the presented price, this implies that his/her WTP for the good in question exceeds the chosen bid value, and vice versa (Carson & Hanemann, 2005).

Randomly varying the price presented to respondents, this approach gathers information regarding the proportion of respondents who accept or reject the good at each price level. Econometric analysis of the binary response data gathered at each bid value can be used to estimate the WTP distribution (Hanemann, 1984; Hanemann, Loomis & Kanninen, 1991). Though this technique requires larger samples to produce estimates of a given precision than would open-ended items, it is widely considered to be the most appropriate format as it closely approximates the conditions of real world purchase decisions. That is, dichotomous choice items present consumers with the option to purchase some good at a given price, which they must accept or reject (Dixon *et al.,* 1994; Arrow *et al*., 1993). Moreover, this elicitation format greatly reduces the scope for strategic bidding, and may be somewhat familiar to respondents, as use of referenda to inform the process of public goods provision is not uncommon in the real world (Harrison & Kriström, 1995).

This can run for one round (a single bounded dichotomous choice, or SBDC item), or can be followed up with another bid value, creating a double-bounded dichotomous choice (sometimes referred to by the acronym DBDC) item. Though further dichotomous choice items could be included to produce a multiple-bounded dichotomous choice (MBDC) item, this is seldom done as subsequent items tend to erode the credibility of the hypothetical market scenario without greatly increasing the quantity of information it provides (Hanemann *et al*., 1991; Harrison & Kriström, 1995).

Due to their incentive compatibility and realism, Arrow *et al.* (1993) recommend that contingent valuation researchers employ dichotomous choice items in their hypothetical markets. Since 1989, the double-bounded dichotomous choice format has grown increasingly popular, and is now widely regarded to be superior to other formats for most applications (Abdullah, 2009; Carson & Hanemann, 2005; Hanemann & Kanninen, 1998; Hanley & Spash, 1993). Immediately following the initial valuation item, respondents are presented with a second dichotomous choice item, offering the good or program at a different price. The bid value presented to respondents in the follow-up item is dependent on their initial response; respondents who accept the offer in the first round will be presented with a higher price, and those who rejected the offer in the first round will be presented with a lower price (Hanemann *et* al., 1991; Harrison & Kriström, 1995).

In essence, each response to a dichotomous choice valuation item defines a bound on the range of values within which respondent WTP must lie; WTP is either greater than or smaller than the bid amount presented (Hanemann, 1984; Hanemann *et al*., 1991). Where a hypothetical market uses a double-bounded dichotomous choice format, the follow-up item serves to narrow the range of possible WTP values, increasing the precision with which WTP can be estimated. Given that no obvious price exists for the goods evaluated by contingent valuation studies, researchers designing dichotomous-choice items face substantial uncertainty in determining the bid values presented to respondents. Thus, where researchers have limited prior knowledge of the likely WTP distribution, the use of a double-bounded dichotomous choice item provides a measure of insurance against the selection of excessively high or low initial bid values (Hanemann & Kanninen, 1998).

In most hypothetical markets, the inclusion of a 'no answer' option is recommended. This is likely to improve the quality of estimates produced by easing the identification of disinterested respondents, by allowing respondents to express their indifference, and by reminding respondents that they are not obliged to provide a response where they simply cannot value the good (Arrow *et al*, 1993).

Framing the good and constructing the hypothetical market

The first step of a contingent valuation is the definition of the specific environmental good being valued, and the creation of the hypothetical market. Typically, the good is presented as some form of proposed public program or investment (Arrow *et al.,* 1993). A bid vehicle must be chosen, and care must be taken to ensure that the survey contains clear and understandable explanations of the good to be valued, the provision arrangements, and the relevant decision criteria. Where these conditions are not met, the meaning of the responses gathered by the survey is unclear, and they are very unlikely to form the basis for a reliable valuation estimate (Carson, 2000; Schlapfer, 2008).

The explanation of the good being valued and the provision of information regarding the nature of the hypothetical market are referred to as the 'framing' of the good. If the survey responses are to serve as a reliable proxy for real behaviour, then it is of utmost importance that the good be presented in a way that is both sufficiently detailed and easily understood (Arrow *et al.,* 1993; Garrod & Willis, 1999).

To illustrate this process, consider the case of a contingent valuation study seeking to evaluate the environmental damages arising from carbon dioxide emissions. Considering the incentives for strategic misrepresentation that would arise, it is clearly inappropriate to use a 'willingness to accept compensation' measure. As such, some means must be devised for eliciting accurate estimates of how much respondents are willing to pay to prevent CO_2 emissions. Since it would be extremely difficult to design a realistic, believable, and understandable hypothetical market that trades directly in CO_2 emissions, an alternative framing of this good is required. For instance, the hypothetical market could present respondents with a new public emissions-reduction program, which would introduce new regulations on pollution-intensive industries, possibly increasing the price of their outputs. Survey respondents would thus be presented with a detailed account of these regulations, as well as their expected effects. Assuming the use of a dichotomous choice item, they would then be asked if they would vote for the scheme at a stated price. Since a direct payment would be unrealistic in this case, the price of agreeing could be expressed using an increase in taxes, or a rise in electricity and fuel prices as a payment vehicle.

2.4.4: Obtaining representative and aggregate WTP values

The goal of a contingent valuation study is presumably to estimate the aggregate utility effects of some change, or total willingness to pay for some good or service amongst some relevant population. Thus, the response data gathered by the valuation item are used to generate representative measures of respondent WTP which can be aggregated across the relevant population to produce an estimate of total WTP.

Choice of value measure

Economic theory holds that the WTP and WTA measures to be equivalent, so long as the ratio of the respondent WTP to respondent income and the price elasticity of demand for the good in question are both sufficiently small (Perman, Ma, McGilvry & Common, 1994). However, in empirical applications, the WTA measure is seldom used, due to the opportunity that it presents for strategic bidding, the higher incidence of protest bids, and the conceptual difficulties associated with developing hypothetical markets within which most goods can be believably framed using WTA measures (Adaman *et al*., 2011; Arrow *et al*. 1993).

Once the survey process is complete, econometric analysis of the response data obtained by the hypothetical market is used to establish a 'representative' bid value (Hanley & Spash, 1993). In processing the response data, decisions must be made regarding the treatment non-responses, zero-bids and high-bid outliers. The treatment of respondents who did not respond to the valuation item is a complex choice that is a potentially important determinant of the representative WTP value (Byrnes, Jones & Goodman, 1999; Akai & Nomura, 2004). The most common approach to dealing with these respondents is to remove them from the sample. However, this choice could be considered inappropriate in studies using dichotomous-choice elicitation items. If respondents have been presented with the opportunity to purchase the hypothetical good, and have neglected to indicate their preferences, a more conservative option would be to include these individuals as 'No' responses (Akai & Nomura, 2004).

Since the value of the good in question ultimately depends on effective demand, there is no reason to exclude high bids where these represent feasible and genuine responses. Similarly, where zero bids represent sincere valuations, they should be included as reported (Arrow *et al.,* 1993). On the other hand, where these bids do not reflect sincere valuations, their inclusion will distort value estimates, and they should be identified and removed from the data set. There are two main approaches to identifying protest bids. The first approach makes use of statistical 'rules of thumb', classifying all bid values according to their distance (measured in standard deviations) from the mean value. This crude approach is likely to result in the rejection of meaningful bids, and is an inefficient use of the response data (Hanley & Spash, 1993; Perman *et al.*, 2003). The second approach, as recommended by the Arrow panel, is for the survey to include post-valuation items that ask respondents to explain the reasons behind their responses. Gathering such data provides a far more reliable means for identifying protest bids (Arrow, *et al.*, 1993).

Once the response data has been appropriately tidied, analysts estimate the population WTP distribution using econometric analysis. Multivariate regression models are used to produce a series of response-generation functions. These functions estimate the extent to which hypothesised explanatory variables such as household income or respondent education influence the responses elicited by valuation items (Carson & Hanemann, 2005). These functions compute an estimate of an individual's WTP, or the likelihood of their accepting a particular bid in a dichotomous-choice item, as a function of their characteristics. Response functions are thus an indispensable tool for estimating aggregate WTP for some good amongst a population, using data gathered from a non-representative sample (Hanley & Spash, 1993). Further, comparing the WTP-variable relationships implied by the coefficients in a response-generation function with those predicted by economic theory provides a useful measure of criterion validity, which facilitates quality assessment for the valuation process.

Once the WTP distribution has been estimated, a 'representative bid must be chosen. Historically the mean WTP value is the favoured representative bid; however, many analysts prefer using median values, due to their relative insensitivity to high value outliers, which inflate mean values (Harrison & Kriström, 1995). Moreover, median values tend to be lower than mean, and so their use is in line with the 'conservative design bias' recommended by Arrow *et al.,* (1993). Generally, it is regarded as best practice to calculate both mean and median values and to outline the criteria used in selecting between these measures. The problems associated with zero bids and high-value outliers are largely remedied by use of a dichotomous choice valuation item. Studies using dichotomous choice elicitation formats to estimate aggregate WTP thus tend to use the mean WTP, whilst those that are intended to inform/simulate a voting process generally employ the median WTP value (Carson & Hanemann, 2005; Perman *et al.,* 2003).

WTP Aggregation

The representative values taken from the estimated WTP distributions can be used to infer valuation estimates for the population as a whole. There are three major issues to be resolved at this stage. First, a choice must be made regarding the boundaries of the population over which WTP is to be aggregated. In general, the population is either defined to include all individuals deriving utility from the good or program in question, or to correspond with a relevant political or economic boundary (Hanley & Spash, 1993).

The second issue relates to the proper technique for inferring population values from sample data. This can be done in a number of ways, but the generally accepted approach is to multiply the chosen representative WTP value by the number of households in the population (Hanley & Spash, 1993; Perman *et al.,* 2003). The process is complicated somewhat where the sample differs from the population in some systematic fashion. In these cases, a representative population bid can be established by substituting mean population values for explanatory variables into the estimated response generation functions. This population-representative WTP can then be multiplied by the number of households to establish an estimate of aggregate WTP for the population (Hanley & Spash, 1993).

The third issue to be resolved at this stage is the proper treatment of temporally diffuse quantities (Hanley & Spash, 1993; Arrow *et al*., 1993). Contingent valuation studies often seek to evaluate non-market goods producing benefit streams that accrue over time. This is especially relevant to renewable environmental resources, the benefits of which may be effectively perpetual under good management. Decisions must be made regarding the appropriate time-horizon over which these temporally diffuse benefits are to aggregated, and the appropriate rate for discounting values accruing in the future. In many cases, the nature of the goods or benefits being valued will suggest a time horizon; for instance, the environmental benefits produced from preservation of natural ecosystems should be valued as perpetuities, and the benefits produced by renewable-energy installations should be valued over the same time horizon as they are expected to operate (Lumby & Saville, 1995). This is an especially relevant consideration where hypothetical markets spread payments over time using monthly or weekly payments.

2.4.5: Post-valuation assessment of the valuation exercise

Once the valuation exercise has been completed, the quality and reliability of the estimates must be assessed. This will include analysis of factors such as response rate, number of protest or zero bids, and comparison of the covariate relationships with those suggested by economic theory. The value estimates produced must also be compared with those produced by comparable past studies, especially those using alternative methodologies as this facilitates assessment of their convergent validity (Hanley & Spash, 1993).

2.4.6: Problems with the Contingent Valuations Methodology

As the popularity of contingent valuation has grown, so too has criticism of it. Many economists mistrust the methodology, arguing that the value estimates it produces are hypothetical, biased, and devoid of useful meaning (Diamond & Hausman, 1994; Arrow *et al*., 1993). Clearly, the reliance on data collected using public surveys makes contingent valuations prone to numerous forms of bias, and much of the literature related to the application of contingent valuation concerns methods for identifying, and dealing with the most common forms of bias (Carson& Hanemann, 2005; Arrow *et al*, 1993; Schlapfer, 2008).

Biases can arise both in the administration of the survey, and from elements of the survey itself. Factors such as the conduct and disposition of interviewers, the context in which surveying occurs, the mode of survey administration, the wording of questions, the choice of payment vehicle, the information provided, and the believability of the hypothetical market all have the potential to induce bias in respondent valuations (Arrow *et al*., 1993). This section examines the most common forms of bias encountered in the conduct of contingent valuations and, where appropriate, discusses popular methods for measuring, avoiding, and minimising them.

Strategic Bias

Strategic bias refers to the tendency for respondents to distort their responses to valuation items in pursuit of some desired outcome. If respondents expect their bids to influence future policy, they may find it advantageous to distort or misrepresent their true preferences (Hanley & Spash, 1993; Abdullah, 2009). For instance, if respondents believed that their stated WTP bids were likely to actually be collected at some point, they would have an incentive to understate their true WTP. Conversely, where the respondents assume that payments will not be collected, they may bid values above their true WTP, hoping to steer decisions towards their preferred outcomes for free (Arrow *et al*. 1993). The likelihood of strategic bias amongst respondents thus depends on the perceptions they hold with regard to the payment obligations and decision criteria involved in the survey. Strategic bias is most likely to arise in valuation studies related to emotive subjects on which respondents have well established and strongly-held preferences. By exaggerating their support for, or opposition to the proposed program, respondents may attempt to influence the results of the survey in their favoured direction (Georgiou, Whittington, Pearce & Moran, 1997; Garrod & Willis, 1999; Carson & Hanemann, 2005). Strategic bias is largely eliminated by the use of dichotomous choice elicitation formats with coercive payment vehicles. These items are said to be incentive compatible, in that respondents presented with a valuation item of this type have no opportunity to promote their preferred outcomes through misrepresentation – their optimal strategy is to answer the question truthfully (Hanley & Spash, 1993; Carson & Hanemann, 2005; Arrow *et al*., 1993).

Payment Vehicle Bias

Where the payment mechanism specified in the hypothetical market is controversial or in some way provocative, this may induce bias in the responses to the valuation item, which thus become a poor measure of respondent preferences. For instance, a respondent, feeling that he already pays too much tax, may refuse a dichotomous-choice offer in a hypothetical market using tax-based payment, even where the program in question provides a desired service at a price below their true WTP. In these cases, individuals may respond to hypothetical market responses in a fashion that is more reflective of their aversion to taxation than of their true preferences for the good or program in question. The classical prescription to remedy this bias is to ensure that the chosen payment vehicle is as neutral and uncontroversial as possible (Arrow *et al*., 1993).

However, an alternative perspective rejects the notion of the bid vehicle as a source of bias, instead arguing that the means by which payments are made is an important component of the hypothetical market scenario and a legitimate determinant of respondent WTP (Carson & Hanemann, 2005). In this view, there is no single 'true' value for the good being valued, but rather, a range of possible values, corresponding with the range of possible provision arrangements. That WTP for a particular good or service should vary across payment vehicles should thus be expected. If this view is accepted as valid, then payment vehicle bias can arise only where the hypothetical market employs a means of payment that differs from that which would be used in a real market. The remedy to this problem is thus to utilise the payment vehicle most likely to be used in an actual market, were one to exist (Hanley & Spash, 1993; Carson & Hanemann, 2005; Schlapfer, 2008).

Interviewer Bias

Interviewer bias arises when the presence or conduct of the interviewer affects respondent behaviour in the hypothetical market. Generally, this bias arises when respondents seek to please the interviewer by providing answers perceived to be 'correct' or 'desirable' in place of their own sincere responses. This is sometimes referred to as 'yea-saying' (Abdullah, 2009). Interviewer effects can influence the responses provided to survey items assessing attitudes, behaviours, or demographic covariates, as well as the hypothetical market items.

This bias is especially prevalent in surveys administered through face-to-face interviews, and in studies seeking to value goods or services that are considered to be in some way virtuous or socially desirable (Carson & Hanemann, 2005; Arrow *et al*., 1993). Interviewer biases can be reduced by standardising the survey administration process to ensure that the framing of questions and conduct of the interviewer do not imply a preference for a particular answer. Further, care should be taken to emphasise that the survey is about opinions, and that there are no 'right' or 'wrong' answers. The absence of interviewer effects is one of the major advantages to using self-administered printed surveys, which are typically conducted through the post (Hanley & Spash, 1993).

Starting Point (anchoring) Bias

'Anchoring' is the term used to describe the tendency for the prices and values suggested to respondents during the course of the survey process to affect the valuations they provide (Abdullah, 2009). This bias is most prevalent in elicitation formats that present respondents with multiple valuation items, such as payment cards, or double-bounded dichotomous choice, and is notably absent in open-ended valuation items (Hanley & Spash, 1993; Arrow *et al.*, 1993).

For instance, consider a respondent participating in a hypothetical market using a double-bounded dichotomous choice valuation item. The respondent has an initial WTP of R50 for the good, and is presented with a first bid value of R20, which is accepted. If this respondent then enters the follow-up round with a WTP of R20, then they are said to have 'anchored' their responses to the initial bid. Where this occurs, hypothetical market responses will misrepresent a respondent's true preferences.

This bias is most likely to arise where the good being valued is novel and unfamiliar to respondents, who may thus have poorly developed preferences for the good (Abdullah, 2009). Without a ready standard by which to confirm their initial valuations as sensible, they may anchor their expectations of what such a good or program 'should' cost to the initial price at which it is presented. This explanation is especially compelling if the good being traded in the hypothetical market is credibly and realistically framed.

Although starting-point biases are difficult to prevent in studies using double-bounded dichotomous choice or payment card valuation items, they are easily detected by comparing the WTP distributions of respondents at each starting bid.

Mental Account Bias

Sometimes called the 'embedding effect', mental account bias refers to the tendency for the responses elicited by valuation items to be largely invariant to the scope of the good being valued. This effect is most evident in cases where respondents indicate very similar WTP values for individual goods or amenities and for larger composite goods which include them (Arrow *et al.,* 1993). This phenomenon has been speculatively attributed to the tendency of individuals to implicitly assign portions of their income to various 'mental accounts' (Diamond & Hausman, 1994). Thus, the responses provided to valuation items may be more reflective of their mental accounting procedure, and the spending allocated to the 'environmental goods' account, rather than of their sincere valuation of the good in question. A classic example of this bias was observed in experiments conducted by Desvouges (1993), who sought to evaluate the WTP for measures that would protect marine birds, with the program described in different survey versions as preventing the deaths of 2000, 20 000 or 200 000 sea birds. The results from this study found responses to the valuation items to be remarkably insensitive to these changes, even though the damage specified in the hypothetical scenarios increase one hundredfold (Diamond & Hausman, 1994).

The bias caused by embedding is of major concern to the valuation process, as it casts doubt on the conception of responses to hypothetical market scenarios as a reliable guide to real-world behaviours (Diamond & Hausman, 1994). Ultimately, the embedding bias may arise from a tendency amongst respondents to provide responses based on the value that they place on the 'warm glow' feelings that they get from agreeing to undertake socially beneficial actions (Hanley & Spash, 1993).

Hypothetical Bias

In a real market, all purchases carry an obvious opportunity cost; buying a good implies a reduction in funds available for the purchase of other goods. This cost acts as a form of punishment where respondents do not adequately consider their preferences, and agree to purchase a good for a price that exceeds their true maximum WTP for it. Since there is no equivalent penalty mechanism operating in the hypothetical market, critics have argued that respondents are unlikely to expend the same time and effort in considering their true willingness to purchase a good at a stated price than they would do for an identical purchase in a real market (Diamond & Hausman, 1994; Schlapfer, 2008). Further, contingent valuation studies almost invariably utilise payment vehicles that operate prospectively; that is, respondents are asked to agree to a purchase now, with payment usually being collected at a later point through taxes, user-fees or price changes.

Thus, respondents operating in hypothetical markets are not required to immediately reduce their expenditure on other goods in order to increase their spending on the good being valued. As such, respondents may overstate their true WTP for the good, as they have no incentives to fully consider the trade-offs involved in the purchase when formulating their valuation responses (Akai & Nomura, 2004). Though similar to strategic bias and interviewer bias, this overstatement arises from a failure to expend sufficient effort in considering the choice presented by the hypothetical market, rather than from any wilful deception.

2.4.7: Is Contingent Valuation suitable for use in Developing Countries?

As a final consideration, it should be noted that most of the widely accepted practical guidelines for conducting contingent valuation studies are based on the experience of researchers working in the United States, Western Europe or Japan. As such, some guidelines may require modification or may not apply when working in the developing world. Cultural factors are of particular relevance; people may be averse to placing monetary values on some goods, or may regard discussion of certain topics – household income, for instance – to be inappropriate (Adaman *et al.,* 2010). Further, respondents in developing countries may be inexperienced with public opinion surveys, and may lack the literacy and English skills required to fully comprehend the scenario presented by the survey. Though skilled translators could solve this problem, they are often expensive or unavailable (Abdullah & Jeanty, 2012). Cultural barriers may also make some groups of people difficult to approach, or unwilling to participate in the study. For example, the prevalence of interpersonal crime in South Africa may make people less willing to engage with strangers, including researchers.

Further, using contingent valuation as a guide for valuing public goods and spaces implies a normative assumption that WTP/WTA is an appropriate measure of consumer utility and social value. These metrics grant wealthier respondents a proportionately greater share of the decision making power as a result of their greater ability to pay; thus, using these metrics implies an endorsement of the prevailing income distribution as just (James, 1994). However, where non-trivial proportions of the population have little or no money income, the monetary valuations attached to particular goods and services may provide an inadequate reflection of the true social utility they produce. Where people have no money to spend, it is obviously fallacious to use their willingness to pay as a measure of their preferences – a man does not value nothing, simply for having no money to spend. Further, where such measures are used to inform the provision of public goods and services, they are likely to favour those goods and services preferred by the wealthy.

Thus, contingent valuation is inappropriate for use in many applications in developing countries. Where contingent valuation studies are undertaken in developing-world context, care must be taken to ensure that the study considers the relevant cultural factors, and that the survey is presented in a way that makes it accessible to its intended audience.

Chapter Three: Literature Review

Contingent Valuation in Practice

Chapter 3 undertakes a review of the existing literature related to the estimation of household WTP for green electricity products.

Though it is one of the less developed branches of the environmental valuation literature, a number of studies from around the world have used the contingent valuation approach to estimate the demand for green electricity products. This literature review examines a selection of these studies, as listen in Table 3.1 When choosing the studies included in this review, priority was given to valuation studies conducted in a developing market context. Green electricity valuation studies selected for this review include: American studies (Ethier, Poe, Schultze, & Clarke, 2000; Zarnikau 2003; Byrnes *et al*., 1999; Wiser, 2007; Borchars, Duke & Parsons, 2007), an Australian study (Ivanova, 2012), European studies (Gerpott & Mahmudova 2011; Bollino, 2009), and a study conducted in Japan (Akai & Nomura, 2004). The selected body of green electricity valuation studies from the developing world include studies conducted in Turkey (Adaman *et al*., 2011), South Korea (Seung-Hoon & So-Yoon, 2009), Chile (Aravena-Noviella *et al*., 2010), Kenya (Abdullah & Jeanty, 2012), and South Africa (A.C. Neilson, 2002; Oliver *et al*., 2011).

This literature review is composed of three sections. Section 3.1 examines the aspects of the methodology employed by each of these studies. This is followed by Section 3.2, which discusses the respondent characteristics that past studies have included as explanatory variables, and identifies covariates that could be suitable for inclusion in this study. Section 3.3 concludes this review with a summary of three of the chosen studies that were notable for their originality in applying the contingent valuation methodology. The review presented in this Chapter is summarised in Tables 3.1 and 3.2.

Table 3.1: Summary of the methodologies adopted by reference studies in developed economies.

Study	Location	Survey Mode	N	Elicitation format	Framing of the good	Payment Mechanism
Byrnes *et al.* (1999)	Colorado, USA	Telephone + Mail	600	DBDC	Increased use of green electricity (20MW)	Flat-rate increase in utility bills
	Wisconsin, USA	Telephone + Mail	500		1.3MW Solar PV arrays for 72 local school	Monthly subscription payment
Ethier *et al.* (2000)	Buffalo, New York	Telephone Mail	386 424	SBDC (calibrated)	Utility green electricity investment program	Monthly subscription payment
Zarnikau (2003)	Texas	Written survey & Deliberative Poll	2800	Open-ended	Increased use of green electricity and energy efficiency measures	Flat rate increases in utility bills.
Akai & Nomura (2004)	Japan	Mail	1000	DBDC	Increased use of green electricity	Flat rate increase in utility bill
Borchars *et al.* (2007)	Delaware, USA	Face to Face interviews	128	Payment cards	Increased use of green electricity	Higher electricity prices
Wiser (2007)	USA	Mail Survey	1574	SBDC	Increased use of green electricity through public/private provision	Flat rate increase in utility bill
Bollino (2009)	Italy	Online survey	1601	Payment cards	Increased use of green electricity	Flat rate increase in electricity bill
Gerpott & Mahmudova (2010)	Germany	Telephone	238	Payment Cards	Green electricity from renewable sources	Higher electricity prices
Ivanova (2012)	Queensland, Australia	Mail	820	Open Ended 'Ruler' format	Increased use of green electricity	Higher Electricity Prices

<u>Table 3.2:</u> Summary of the methodologies adopted by reference studies in developing economies

Study	Location	Survey Mode	N	Elicitation format	Framing of the good	Payment Mechanism
Oliver *et al*. (2011)	Cape Peninsula	Telephone	405	Open Ended	Green electricity from renewable sources	Higher electricity prices
Seung-Hoon & So-Yoon (2009)	Korea	Face to Face interviews	800	DBDC	Public Fund to increase RET use to 7% of electricity used.	Flat-rate increase in utility bills
Aravena-Noviella *et al*. (2010)	Chile	Face-to-face	726	DBDC	Upcoming referendum on green electricity vs. conventional technologies	Flat rate increases in monthly bid
Adaman *et al*. (2011)	Turkey	Face-to-face	2422	DBDC	Contribution to a national/global fund to promote green electricity and energy efficiency	Once-off donation
Abdullah & Jeanty (2011)	Kenya	Face to Face interviews	200	DBDC	Installation of household solar PV panels	Once-off payment or Monthly Payment

3.1: Survey design and Data Collection

Many of the chosen reference studies seek not only to evaluate the aggregate magnitude and individual determinants of WTP, but also to explicitly consider the manner in which specific changes to the provision scenario affect estimates of WTP. These include the use of public vs. private provision arrangements (Wiser, 2007), use of voluntary vs. mandatory adoption (Wiser, 2003), provision by a national vs. international body (Adaman *et al*., 2011), and differences in the specific electricity technologies employed in the scenario (Abdullah& Jeanty, 2012; Borchars *et al*., 2007).

Survey Mode

The mode of survey administration employed by these studies was dominated by postal surveys (Byrnes, *et al.,* 1999; Akai & Nomura, 2004; , 2012; Ethier *et al*., 2000), face-to-face interviews (Aravena-Noviella *et al*., 2010; Borchars *et al*., 2007; Adaman *et al*., 2011; Abdullah& Jeanty, 2012), and telephonic interviews (Oliver *et al.*, 2011; Byrnes *et al.*, 1999). Only Bollino (2009) chose to use an alternative administration mode, conducting their survey on the internet.

The results from the reviewed studies confirm many of the expected trends in survey mode choice; mail surveys generally reached large samples, though at times they suffered from low response rates (Akai & Nomura, 2004; Ivanova, 2012). Studies using telephonic surveys and face-to-face interviews generally attained higher rates of participation and survey completion than other approaches. Despite the high cost of using face-to-face surveys, some studies did gather impressively large samples in this manner. Notable in this regard is Adaman *et al*. (2011), obtained a sample of 2422, and a response rate of 88% in their survey of Urban Turks.

Elicitation Format

The elicitation formats employed by the valuation items in the chosen studies appear to weakly confirm the declining popularity of open-ended WTP items in favour of dichotomous choice formats. Open-ended items were used to elicit valuations by three of the studies included in this review (Zarnikau, 2003; Ivanova, 2012; Oliver *et al*., 2011). By contrast, dichotomous-choice type items were used by eight of the studies; six of these used the double-bounded format (Byrnes *et* al., 1999; Akai & Nomura, 2004; Seung-Hoon & So-Yoon, 2009; Adaman, *et al*., 2011; Abdullah, 2011; Aravena-Noviella *et al*., 2010), and two studies opted for a single-bounded valuation item (Wiser, 2007; Ethier *et al*., 2000). Finally, three studies (Bollino, 2009; Borchars *et al*., 2007; Gerpott & Mahmudova, 2010) made use of payment cards to elicit valuations.

Payment Vehicle

Without exception, the hypothetical markets presented by the chosen studies used payment vehicles that operated either through increased utility bills, or contributions to a green electricity fund of some kind. Increased utility-bills were used as a payment mechanism by nine of the studies included in the review. Of these studies, Oliver *et al.* (2011), Gerpott & Mahmudova (2011), Ivanova, (2012), and Borchars *et al.,* (2007) framed the price as a rise in electricity prices, or a proportional increase in electricity spending. Flat-rate increases in electricity bills were used by Byrnes *et al*. (1999), Akai & Nomura (2004), Aravena-Noviella (2010), Seung-Hoon & So-Yoon (2011), and Ivanova (2012).

Ethier *et al.* (2000), Abdullah (2011), Adaman *et al*. (2011) and Byrnes *et al*. (1999) elected to avoid use of utility bills as a payment vehicle, preferring to frame purchases as subscriptions or contributions to specially-designed green electricity funds. Byrnes *et al*. (1999) and Ethier *et al*. (2000) frame these contributions as monthly payments, whilst Abdullah & Jeanty (2011) and Adaman *et al.* (2011) make use of both “once-off payment” and “monthly-payment” framings.

Table 3.3: Summary of results obtained by reference studies

	Study	Location	Survey Mode	N	Response Rate	Respondents with WTP>0	Mean WTP
Studies from Developed Economies	Byrnes *et al.* (1999)	Colorado, USA	Telephone + Mail	600	0.59	82%	US$2.10
		Wisconsin, USA	Telephone + Mail	500		64%	US$2.69
	Ethier *et al.* (2000)	Buffalo, New York	Telephone	386	0.71	31%	US$ 6.00
			Mail	424	0.67	36%	
	Zarnikau (2003)	Texas	Written survey & Deliberative Poll	2800	Not reported	50%	US$5.39
	Akai & Nomura (2004)	Japan	Mail	1000	0.37	>50%	US$ 17 (median)
	Borchars *et al.* (2007)	Delaware, USA	Face to Face interviews	128	0.34	61%	US$8.92 - $19.03
	Wiser (2007)	USA	Mail Survey	1574	>0.45	53%	Not reported
	Bollino (2009)	Italy	Online survey	1601	----	47%	€2.34 - €9.39
	Gerpott & Mahmudova (2010)	Germany	Telephone	238	0.72	54.3%	5-10% increase
	Ivanova (2012)	Queensland, Australia	Mail	820	0.26	>80%	AUS $7.32-$9.33
Studies from developing economies	Oliver (2009)	Cape Peninsula	Telephone	405	0.81	42%	ZAR 117.67
	Seung-Hoon & So-Yoon (2009)	Korea	Face to Face interviews	800	>0.95	26.3%	US$ 1.80 - $2.20
	Aravena-Noviella *et al.* (2010)	Chile	Face-to-face	726	Not reported	Not reported	US $ 8.54
	Adaman *et al.* (2011)	Turkey	Face-to-face	2422	0.88	64%	US $ 117 (once off)
	Abdullah & Jeanty (2011)	Kenya	Face to Face interviews	200	1.00	40%	US $8.16

3.2: Covariate Relationships

This section of the literature review examines the factors included as explanatory covariates by the selected reference studies. Though the number and choice of covariates examined varies widely between studies, most of the studies reviewed do have a few key covariates in common. Table 3.4 & 3.5 provide a summary of the statistically significant WTP-covariate relationships observed in each of the studies included in this review.

Section 3.2 assesses some of the characteristics popularly included as explanatory covariates in green-electricity valuations. This assessment examines popular and notable approaches to measuring each variable, and explains the nature and direction of the expected WTP-covariate relationship. Demographic variables are examined first, followed by psychographic/attitudinal variables, and then behavioural variables.

3.2.1: Demographic Variables

Disposable Household Income

Disposable income is expected to be positively related to WTP for green electricity. Higher income individuals are expected, ceteris paribus, to have higher WTP, not only because of their greater ability to pay, but also because green electricity is a luxury good.

Income was included as a covariate by nearly all of the reference studies examined in this review (see Table 3.4 & 3.5), with the sole exception of Akai & Nomura (2004). A positive relationship between income and WTP for green electricity was observed in all studies, and this relationship was found to be statistically significant in the majority of these studies (Roe, *et al*.,2001; Zarnikau , 2003; Ivanova, 2012; Wiser, 2007; Bollino, 2009; Sueng-Hoon & So-Yoon, 2009; Oliver *et al.*, 2011; Aravena-Noviella *et al*., 2010; Abdullah & Jeanty, 2012; Adaman, *et al*., 2011).

Income is widely regarded to be somewhat trickier to measure using survey items than most other demographic characteristics. Many respondents consider financial matters to be sensitive or private, and survey items that respondents find invasive are thus likely to experience high non-response rates (Adaman *et al.,* 2011). Designing income-measurement items thus involves a trade-off; more detailed items provide richer data, but lower response rates. Item non-response creates statistical issues such that even a small drop in response rates may outweigh the benefits of a richer dataset (Arrow *et al.*, 1993; Moore Stinson & Welnaik, 2001).

Further, the accuracy of self-reported income measures is questionable. Research indicates that the general tendency of survey findings is to understate income, primarily due to different understandings of what constitutes 'income' (Moore *et al.*, 2001). Under-reporting is most common for income derived from asset ownership and sporadic employment, whilst regular income from wages, salaries, pensions and (to a lesser extent) transfers are generally more accurately reported. The view that the under-reporting of income is generally small (around 5%) is widely endorsed (Moore *et al.*, 2001). To avoid these issues, it is common practice to elicit income data using an item that asks respondents to indicate which of several monthly income brackets their household falls into (Oliver *et al.*, 2011; Zarnikau 2003; Ivanova, 2012). So long as the income brackets are appropriately spaced, a categorical item of this type will generally provide a suitable compromise between precision and privacy.

An interesting alternative approach to gathering income data is offered by the Adaman *et al.* (2011) study conducted in Turkey. Many Turkish households are openly hostile to the government, and tax evasion is common. As such, respondents were found to be deeply distrustful and suspicious of researchers asking for data related to their income or wealth. To avoid the bias that non-response and strategic misrepresentation would likely produce, the researchers instead drew up an inventory of assets such as cars, air conditioners, etc. Data regarding ownership of each item was collected and compiled into an 'asset ownership' variable, which was employed as a proxy for income.

<u>Monthly electricity spending</u>

The relationship between WTP for green electricity and household spending on electricity suggested by economic theory is ambiguous. Households with higher electricity consumption are responsible for a proportionately greater share of the environmental damages produced by the generation of electricity. If the decision to purchase green electricity is motivated by normative factors, such as a desire for justice or fairness, then this would suggest that WTP for green electricity would be positively related to electricity spending (Zaman, Miliutenko & Nagapetan, 2010). Further, where green electricity products collect payment through a fixed monthly charge rather than an increase in unit-prices, the proportional price premium implied by this charge will vary negatively with current spending.

Conversely, there are reasons to expect that WTP for green electricity will be negatively related to household electricity spending. High monthly electricity spending could arise from a general apathy and indifference to electricity consumption and its costs, especially where electricity spending accounts for a small share of income. Where households are apathetic and wasteful in their use of electricity, they are highly unlikely to adopt a green electricity product.

Gathering electricity spending data using surveys is complicated, as many respondents may be genuinely unsure of their household's monthly electricity spending. This most likely arises from the typically low levels of consumer engagement and involvement in its purchase (Gerpott & Mahmudova, 2011). Households receiving monthly utility bills often make payment using debit orders, and so may have a vague or outdated idea of how much they spend. Households who purchase their electricity through a prepaid meter make payments at irregular intervals, and may struggle to accurately estimate their monthly spending.

Of the reference studies included in this review, only Gerpott & Mahmudova (2011) found household electricity spending to be a significant (negative) predictor of WTP.

Age

Age is expected to be negatively related to WTP for green electricity and for environmental preservation goods more broadly (Wiser, 2007). This is partly for selfish reasons; since younger people have longer expected lifespans, they have a correspondingly greater stake in averting environmental deterioration and preserving the planet in a hospitable condition. Further, older people tend to be more set in their habits and preferences, and so are less likely to consider adopting new products featuring novel technologies than their younger counterparts (Diaz-Rainey & Tzavara, 2005). Finally, the public profile of environmental preservation causes has grown rapidly over the past few years. Environmental issues are now a popular topic in the media, and have been a fixture in many primary and secondary school curricula for some time now (Straughan & Roberts, 1999). Environmental products may thus be more accessible to younger people on account of their greater exposure to environmental causes and ideas. Age was examined by twelve of the fourteen studies examined in this review. A negative relationship between age and WTP for green electricity was found in all cases, and this relationship was statistically significant in nine studies (Byrnes *et al., 1999;* Roe, *et al*., 2001; Zarnikau , 2003; Borchars *et al.,* 2007; Wiser, 2007; Oliver *et al*., 2009; Aravena-Noviella *et al*., 2010; Gerpott & Mahmudova, 2011; Adaman, *et al*., 2011; Ivanova, 2012).

<u>Gender</u>

Economic theory provides no reason to expect respondents of either sex to have a greater WTP for environmental goods. However, a number of studies in the environmental valuation literature have found women to display higher levels of interest in, and demand for environmentally friendly products. The reasons for this trend are unclear, but it is sometimes attributed to the more caring, empathetic and altruistic roles typically associated with female identity (Diaz-Rainey & Tzavera, 2005; Straughan & Roberts, 1995).

The relationships observed between respondent sex and WTP for green electricity in past studies have been mixed. Respondent sex was examined as a covariate by five of the fourteen studies included in this review (Borchars *et al.,* 2007; Wiser, 2007; Bollino, 2011; Aravena-Noviella *et al*., 2010; Adaman, *et al*. 2011), but statistically significant relationships were observed in only two of these. Bollino (2009) found WTP to be significantly higher amongst men, whilst Wiser (2007) found WTP to be significantly higher amongst women.

<u>Education</u>

Respondent education is hypothesised to be positively related to WTP for green electricity. That more educated individuals tend to express stronger preferences for environmental protection goods is a widely accepted finding, supported by research from the fields of economics, marketing and psychology (Arkesteijn & Oerlemans, 2005; Masini & Menichetti, 2010; Ozaki, 2010). However, considering the variety of factors that could plausibly moderate the relationship between education and WTP for environmental goods, it is unsurprising that the strength of the observed relationship varies widely.

Education is expected to play a particularly important role as a determinant of WTP for novel or unfamiliar environmental goods, of which green electricity is prime example. This is because the nature and extent of the environmental benefits being evaluated may not be widely known, and may remain somewhat uncertain. More educated respondents are likely, in the aggregate, to be more familiar with these benefits, and may be more receptive to new information presented in the survey. Further, more educated respondents may engage more fully with hypothetical market scenarios, on account of their being more practiced in abstract thinking.

Education was included as an explanatory variable by ten of the fourteen studies examined in this review (Byrnes *et al., 1999;* Roe, *et al*., 2001; Zarnikau , 2003; Borchars *et al.,* 2007; Sueng-Hoon & So-Yoon, 2009; Aravena-Noviella *et al*., 2010; Bollino, 2009; Adaman, *et al*., 2011; Ivanova, 2012). A statistically significant positive relationship between education and respondent WTP was observed in all studies except Seung-Hoon & So-Yoon (2009) and Wiser (2007).

Whilst the 'highest qualification attained' is convenient and widely used measure of educational achievement, it is problematic, as it implies a strict equivalence between qualifications of equal 'rank'. For instance, this measure would imply that everyone who selected 'bachelor's degree' as their highest qualification is equally educated. The ordinal nature of the highest-qualification measure complicates its inclusion in statistical models; though there is a reasonably well-defined ranking of academic and technical qualifications, the incremental change in education represented by a movement between adjacent categories differs widely. A common approach to dealing with these issues is to recode the survey categorical responses into a new continuous variable that takes a value equal to the minimum number of years of education required to attain their indicated qualification.

3.2.2: Psychographic Variables

A large body of research findings now support the conclusion that psychographic characteristics such as environmental norms, perceived consumer efficacy and particular attitudes/beliefs serve as somewhat more reliable predictors of 'green' consumer behaviours than demographic characteristics such as age, income or education (Arkesteijn & Oerlemans, 2005; Rundle-Thiele, Paladino & Apstoll, 2008; Oliver, 2009). This is unsurprising; considering that the use value of 'green' goods is generally identical to that of 'grey' alternatives, an individual's willingness to pay premium prices for environmentally-friendly products is directly dependant on their internal normative deliberations. The attitudes, perceptions, and beliefs that respondents hold regarding these benefits are thus likely to be a key determinant of WTP for green electricity (Straughan & Roberts, 1999; Zaman *et al*., 2010).

This section examines a number of psychographic traits popularly included as explanatory covariates in the green electricity valuation literature.

Environmental Norms

From a micro-economic perspective, it is curious that consumers would voluntarily choose to pay a premium price for goods on the basis of perceived social or environmental merits. Many of the benefits associated with purchasing 'free range' eggs, 'fair trade' coffee, or 'organic' produce do not accrue to the user. As such, the demand for these goods must arise from the outcome of some internal deliberation based on individual attitudes and values (Straughan & Roberts, 1999; Rundle-Thiele *et al.,* 2008).

Research on green consumers conducted by Zaman *et al*., (2010) indicates that the purchase of 'green' goods is often ultimately motivated by conceptions of fairness, equity, or justice. By purchasing a green product in place of a functionally-equivalent alternative at a lower price, consumers are effectively volunteering to bear a greater share of the real social cost of the good than the market requires of them. Thus, an individual consumer's willingness to pay for premium-priced green electricity is likely to be heavily dependent on the extent to which they perceive the responsibility for environmental protection to be rightly theirs. The values that individuals hold with regards to the environment are referred to as their 'environmental norms'.

Environmental norms were included as a covariate by six of the fourteen studies examined in this review (Oliver *et al.*, 2011; Roe *et al*., 2001; Byrnes *et al*., 1999; Gerpott & Mahmudova, 2011; Adaman *et al.*, 2011; Ivanova, 2012). Environmental norms were found to be positively related to WTP in all cases, and this relationship was statistically significant in all cases, with the sole exception of Adaman *et al.* (2011).

Following Wiser (2007), Gerpott & Mahmudova (2011) offer a variation on the usual environmental norms variable by examining the effects of perceived social norms on an individual's choice to adopt green electricity. Respondents were asked to indicate how they believed their social reference groups would respond to their choice to (not) purchase green electricity. Respondents who believed that their social reference groups would approve of their signing up for a green electricity product were found to be far more willing to pay for one.

This trait is generally measured using opinion items that ask a respondent to agree or disagree with statements of opinion that correspond to particular normative positions, either in a binary form or using Likert scales (Wiser, 2007; Roe *et al.,* 2001).

<u>Climate Change Attitudes</u>

The demand for premium-priced green electricity products amongst household consumers is assumed to be derived from their demand for the environmental improvements associated with reduced use of fossil fuels (Adaman *et al.,* 2011). For those consumers who are concerned about the effects of anthropogenic climate change, a non-trivial share of this value is likely to be accounted for by reduced CO_2 emissions. Thus, the attitudes and perceptions that respondents hold with regard to climate change are likely to be a key determinant of their willingness to purchase a green electricity product at a premium price.

Three aspects of a respondent's beliefs and attitudes regarding climate change are assumed to be of particular relevance as determinants of WTP for green electricity. Firstly, respondents must be informed about climate change, and the environmental consequences thereof. Secondly, the respondent must be concerned about the effects of climate change. Finally, respondents must consider climate change to be an anthropogenic phenomenon. Where respondents meet these three criteria, their preferences are expected to favour low-emission electricity products. Where respondents are unaware of or unconcerned by climate change, they are unlikely to be willing to pay for measures to avert it. Where respondents are aware of climate change but not unconcerned about it, or where respondents consider human actions to be a negligible contributor to climate change, the incentive for respondents to voluntarily pay for emission-reductions are unclear.

Knowledge of climate change and other environmental issues was included as an explanatory variable by five of the fourteen studies examined in this review (Byrnes *et al.*, 1999; Borchars *et al.,* 2007; Ivanova, 2012; Oliver *et al*., 2011; Adaman *et al.,* 2011). This relationship was found to be statistically significant in all cases, except Ivanova (2012).

Attitudes towards Renewable Energy Technologies

The purchase of a green electricity product is the expression of an individual's demand for the environmental benefits produced by reducing the use of fossil fuels. Not only are these benefits geographically and temporally diffuse, they are also counterfactual in nature (Gerpott & Mahmudova, 2011). That is, they produce gains by averting further environmental degradation, and the magnitude of these gains can only be measured relative to some speculative alternative future scenario. Many components of these benefits are thus necessarily notional from a consumer perspective, as they are not just difficult, but impossible to observe. As such, consumers are forced to take many of the claimed environmental benefits of purchasing green electricity products on faith (Aravena-Noviella *et al.,* 2010; Bergman, Hanley & Wright, 2006). It thus follows that a respondent's WTP for premium-priced green electricity products will be largely determined by the extent to which they are familiar with renewable energy technologies and aware of the benefits they produce, as well as the extent to which they believe these benefits to be real (Seung-Hoon & So-Yoon, 2009). If respondents are willing to pay to protect the environment and prevent environmental damage, this will only translate into a demand for green electricity products where renewable energy technologies are regarded as an effective and sensible means of achieving this.

Three factors are considered to be of particular importance as determinants of WTP. The first of these is awareness of renewable energy technologies. Respondents who are not familiar with the renewable energy technologies and the benefits they produce are unlikely to be willing to pay premium prices for green electricity products. The second key factor is the respondent perceptions of renewable energy technologies. Many people have very low opinions of renewable technologies (Zarnikau, 2003). These poor perceptions are usually related to their intermittency of supply, their high generation costs, and the adverse impacts that some technologies – particularly wind farms - have on the landscape and birdlife of the surrounding area (Menzies, 2011). Individuals who hold negative views of renewable energy technologies are likely to have lower WTP for green electricity products, even where they do desire the environmental improvements that reduced coal use would produce. The third factor is confidence in the potential for renewable energy technologies to be major sources of electricity in the future. Most renewable technologies are still in their developmental stages, and with the sole exception of large-scale hydropower, they all remain immature in their use as grid-supply technologies. Thus, individuals who express confidence that the performance of these technologies will probably improve over time perceive an additional stream of benefits accruing from the purchase of green electricity (Akai & Nomura, 2004). These respondents are thus likely to have higher WTP for green electricity products than respondents who do not perceive this benefit stream, due to their neutrality or low confidence in the prospects for renewables to mature into competitive generation technologies.

Respondent knowledge of renewable energy technologies was included as a covariate by nine of the fourteen reference studies included in this review (Zarnikau , 2003; Akai & Nomura, 2004; Borchars *et al.,* 2007; Wiser, 2007; Sueng-Hoon & So-Yoon, 2009; Bollino, 2009;Aravena-Noviella *et al*., 2010; Oliver *et al.,* 2011; Ivanova, 2012). One study (Bollino, 2009) found a significant negative relationship, and two studies (Seung-Hoon & So-Yoon, 2009; Ivanova, 2012) found an insignificant relationship. The remaining six studies observed the expected significant positive relationship between awareness of renewable energy and respondent WTP.

Attitudes towards renewable energy sources were included as a covariate by four of the reference studies (Byrnes *et al.,* 1999; Akai & Nomura, 2004; Oliver *et al.,* 2011; Ivanova, 2012), and a significant positive relationship was found in all cases. The results obtained by Akai & Nomura (2004) indicate that respondents who did not believe that renewable energy sources would be major sources of electricity in the future had a mean WTP for green electricity of approximately zero.

Perceived Consumer Efficacy

Even where individuals are deeply concerned about anthropogenic climate change and express their support for renewable energy technologies as a viable means of addressing it, this will only translate into a higher WTP for green electricity if respondents consider their consumption choices to have a meaningful effect on the world (Wiser, 2007). If respondents consider their consumption choices to be insignificant in determining the state of the world, they are unlikely to engage in small acts of consumer activism like purchasing green electricity products. That is to say, low perceived consumer efficacy can effectively decouple an individual's preferences for environmental preservation from their behaviour as a consumer. Conversely, where respondents consider their consumption choices to be an effective means of attaining meaningful changes in the real world, they are far more likely to engage in activist consumerism by purchasing green electricity and similar products. Thus, a positive relationship between perceived consumer efficacy and WTP for green electricity is expected.

Perceived consumer efficacy was included as a covariate by Byrnes *et al.* (1999) and Wiser (2007), and a statistically significant positive relationship was found in both cases.

Participation Expectations

The provision of public goods has long been plagued by the 'free rider' problem. Given that most if not all of the environmental benefits produced by purchasing green electricity are non-excludable in nature, individuals will see utility gains from an increased use of renewable energy technologies, regardless of their status as (non)adopters. Thus, the benefits attained by any individual depend on the total number of households purchasing green electricity, whilst the cost borne by each individual is determined by their own (non)adoption. As such, all individuals have an incentive to 'free-ride', enjoying the benefits produced by green electricity, without having to bear the cost (Adaman *et al*., 2011). Thus, it is expected that an individual's WTP for green electricity products will be positively related to the number of others who they expect would do likewise (Wiser, 2007).

Participation expectations are included as a covariate by Byrnes *et al.*, (1999), Wiser (2007), Oliver *et al.* (2011) and Adaman *et al*., 2011). A significant positive relationship between participation expectations and respondent WTP was observed in all cases.

Perceptions of Nuclear Energy

Purchasing green electricity products realises environmental benefits by reducing the use of fossil fuels, and increasing the use of renewable technologies (Department of Energy, 2010). Considering that increasing the role of nuclear power in the generation mix would imply an equivalent reduction in fossil-fuel use, nuclear power is regarded as a substitute for renewable energy in this regard. However, some people are opposed to the use of nuclear power due to the health and safety risks posed by nuclear leaks, storage of hazardous depleted nuclear fuel, and the potential for catastrophic leaks or meltdowns. Thus, nuclear power will be considered as suitable substitute for green electricity only by individuals who do not regard these risks to be serious. Respondent WTP for green electricity is thus expected to be lower amongst respondents who express pro-nuclear sentiments and attitudes.

Attitudes towards nuclear power are not typically included as a covariate in studies examining WTP for green electricity, and were examined by none of the reference studies included in this review. However, this variable is included in this list, as it is considered to be an appropriate candidate for inclusion as a covariate in this study. The investments currently being planned and undertaken in South Africa involve an explicit choice between nuclear reactors and renewable energy sources (Department of Energy, 2010). This variable may thus provide some relevant and useful information regarding consumer preferences for these technologies.

3.2.3: Behavioural Variables

As noted by Tang & Medhekar (2005), environmental attitudes and values are particularly difficult to measure accurately using surveys, since many respondents may feel pressured to give 'socially desirable' responses that do not reflect their true views or values. The honesty and sincerity of responses to survey items examining attitudes and values is thus difficult to establish, as is the intensity with which these are held.

A potentially more credible alternative measure of a respondent's environmental values is provided by their participation in environmentally conscious, or 'green' behaviours. Green behaviours like membership in environmental organisations, regular visits to national parks, purchasing environmentally-friendly products, or reusing and recycling wastes all provide credible indications of a respondent's environmental values. Green behaviours are expected to serve as potent predictors of respondent WTP for green electricity, as they indicate not only the presence of pro-environmental sentiments, but also that these are of sufficient strength to affect behaviour (Follows & Jobber, 2000; Byrnes *et al*., 1999).

Green behaviours examined as potential covariates by the selected reference studies include the recycling of wastes (Oliver, 2009; Wiser, 2007), regular outdoor activities (Adaman *et al*, 2011), membership of environmental organisations (Roe *et al*, 2001; Aravena-Noviella *et al*., 2010), activism in favour of an environmental cause (Adaman *et al*., 2011), investing in energy-saving appliances (Gerpott & Mahmudova, 2011), and purchasing organic food (Wiser, 2007). Significant positive relationships were found in all cases, with the exception of Aravena-Noviella *et al*., (2010), who could not include this variable in their models, due to near-zero incidence of environmental membership in their sample.

Table 3.4: **Summary of significant WTP-covariate relationships found by reference studies conducted in developed economies**

		Demographic Variables						Psychographic Variables							Provision Scenario	
		Income	Education	Age	Electricity Bill	Household Size	Sex (1= Female)	Environmental Norms	Knowledge of Renewable Energy	Knowledge of environmental issues	Confidence in Renewable Energy	Perceived Consumer efficacy	Participation Expectations	Green Behaviours	Voluntary (+) vs. Mandatory (-)	Private (+) vs. Public (-)Provision
Developed World Studies	Byrnes *et al.* (1999)	ns	+	-				+		+	+	+	+			
	Roe, *et al*. (2001)	+	+	-				+						+		
	Zarnikau (2003)	+	+	-					+							
	Akai & Nomura (2004)								+		+					
	Borchars *et al.* (2007)	ns	+	-			ns		+	+						
	Wiser (2007)	+		-			+					+	+	+	-	+
	Bollino (2011)	+	+	ns			+		-							
	Gerpott & Mahmudova (2011)	ns		-	-	+		+	+					+		
	Ivanova (2012)	+	+	-				+	ns	ns	+				+	

<u>Table 3.5</u> Summary of significant WTP-covariate relationships found by reference studies conducted in developing economies

		Demographic Variables						Psychographic Variables							Provision Scenario	
		Income	Education	Age	Electricity Bill	Household Size	Sex (1= Female)	Environmental Norms	Knowledge of Renewable Energy	Knowledge of environmental issues	Confidence in Renewable Energy	Perceived Consumer efficacy	Participation Expectations	Green Behaviours	Voluntary (+) Payment	Private (+) vs. Public Provision
Developing World Studies	Sueng-Hoon & So-Yoon (2009)	+	ns	ns					ns							
	Oliver *et al*. (2011)	+						+	+	+	+		+	+		
	Aravena-Noviella *et al*. (2010)	+	+	-			ns		+							
	Abdullah & Jeanty (2011)	+	+	ns		ns										
	Adaman, *et al*. (2011)	+	+	-			ns	ns		+			+	+		+

3.3: Review of Notable green-electricity valuation studies

Three interesting variations on the standard valuation-only approach to contingent valuation were provided by Abdullah (2009), and Zarnikau (2003), and Byrnes *et al*. (1999).

Abdullah & Jeanty (2011) sought to examine the WTP expressed by electrified and un-electrified rural Kenyan households for grid-connected electricity and off-grid solar PV panels. This context required researchers to employ somewhat different methods to those used by researchers examining in developed-world consumers who have near-universal access to electricity in their homes. This methodologically-intensive study employed both the contingent valuation and choice experiments approach to examine the different preferences expressed by each group. The choice experiment methodology, sometimes referred to as the 'contingent choice' approach, is a non-market valuation and project planning methodology that is similar to contingent valuation in most respects. The primary difference between these approaches is in the mechanism used to elicit respondent preferences. In place of the hypothetical markets used in contingent valuation, choice experiments present respondents with a number of alternative future scenarios, from which they are asked to select their most preferred. By varying the price of the scenarios presented to respondents, the WTP differences associated with particular changes to the provision scenario can be inferred through econometric analysis. In addition to estimating aggregate WTP for different electricity supply options, this study also sought to measure the utility losses associated with supply outages brought about by the intermittent output from renewable technologies, as well as the grid outages which commonly occur in rural Kenya. In general, their findings indicated a strong preference for grid-supplied electricity in all scenarios, a finding they attribute to the known limitations of the solar-power systems, most notably their intermittent supply.

Zarnikau (2003) undertook an interesting variation on the conventional approach to contingent valuation by assessing the changes in WTP brought about when respondents are provided with extensive information on renewable energy technologies and resource planning. In order to do this, two valuation studies were conducted. The first valuation study was followed by a 'deliberative polling' session, which presented respondents with information about the realistic potential costs and benefits arising from projects to expand the use of renewable energy technologies, or to enhance the efficiency of energy use. The deliberative polls were followed by a second valuation survey. Whilst the provision of such information was found to increase the proportion of the sample who expressed their willingness to pay a modest premium for green electricity, it was also found to decrease the magnitude of the bids provided by supportive respondents. The results indicate that the provision of information produced notable success in moderating the bids offered by high-value outliers. Further, the deliberative polling session produced far larger increases in WTP for energy-efficiency measures than for renewable energy technologies.

The study conducted by Byrnes *et al.* (1999), sought to establish the reliability of contingent valuation a means of estimating real effective demand, by comparing the results of valuation surveys with the behaviour of respondents in simulated real markets. Two initial telephone-based contingent valuation surveys were conducted by utility companies in Colorado and Wisconsin. These surveys sought to evaluate consumer WTP for regionally focused investments in green electricity generation capacity. The hypothetical market scenarios employed by these studies were closely based on real prospective projects. Respondents were informed about these proposed plans, and were asked about their willingness to contribute to the financing these projects by accepting a temporary flat-rate increase in their electricity bill. Respondents who indicated that they would be willing to contribute were told that they would need to register as contributors, and were mailed an information package that explained the investments in more detail. This package also contained a registration card with return postage paid. This card presenting respondents with a few suggested payment values, and asked them to select the amount they would be willing to contribute each month. Since respondents were unaware of the hypothetical nature of the exercise, the act of returning such a registration card provides a far stronger measure of real WTP than a verbal or written agreement to purchase a product at some unspecified point in the future. Overall, 74% of telephone respondents indicated that they would be willing to contribute to the green-investment programs described in the hypothetical market. However, this noble sentiment did not carry through to the simulated market, where only 12.8% of households who indicated their willingness to contribute followed this up by returning a payment card. This result should be a cause for concern to contingent valuation practitioners – a full 87.2% of respondents who replied in the affirmative to the hypothetical market reneged on their commitments when payment was requested. Further, analysis of the pledged payment values found real commitments to be substantially lower than hypothetical market commitment. The results of this study should inspire caution; some 'yes' responses are clearly more credible and valuable than others.

Chapter Four: Study Design

Survey Creation and Data Collection

The contingent valuation in this study uses primary data collected from a survey conducted in Cape Town in early 2012. The survey documents can be found in Appendix A. This chapter explains the decisions made during the development, testing and administration of the contingent valuation survey employed by this study. Many of the choices made relating to experimental design were informed by the literature review presented in Chapter 3. A concise summary of the experimental design choices made by a selection of relevant studies is presented in Table 3.1.

This chapter contains two major sections. Section 4.1 examines process of survey administration and data collection. This begins by defining the bounds of the population sampled in this study, and proceeds with an explanation of the approach taken in administering the survey. The second section discusses the structure, development, and notable attributes of the survey questionnaire, and the hypothetical market employed therein.

4.1: Data Collection

4.1.1: Population of Interest

This study seeks to assess the demand for green electricity products. It thus follows that, the population of interest will include all electricity consumers whose effective demand for these products is positive. The household is considered to be the appropriate sampling unit for use in this study, as electricity services are typically purchased and consumed at household level, rather than by individual agents. The population of interest is thus all households within the Western Cape who could potentially purchase a premium-priced green electricity product.

A broad conception of this population would include all electrified households within the Province. Figures published in the Western Cape Provincial Government's (2010) White Paper on Sustainable Energy indicate that 975 892 (83%) Western Cape households have electricity connections. Since all of these households consume electricity, they could arguably be considered a part of the potential market for green electricity products. However, substantial variations in the financial circumstances facing these households make the realism of this conception questionable.

Low-income households in the Western Cape typically spend a large share (up to 25%) of their income on energy products (Western Cape Provincial Government, 2010). Considering their budgetary constraints, it seems highly unlikely that these households would voluntarily swap their existing electricity supply for a functionally-identical green electricity product at a higher price.

This study thus adopts a more conservative approach, defining the population of interest to include only the 460 448 electricity-consuming Western Cape households classified as 'middle-upper income' (Western Cape Provincial Government, 2010). The aggregate WTP values produced under this conception of the population are thus based on the assumption that each of the 515 444 electrified low-income households has a WTP of zero.

Whilst this choice may exclude some low-income households who genuinely would purchase green electricity, this effect is expected to be relatively small in magnitude. However, it must be noted that, to the extent that this assumption fails, the aggregate valuations produced by this study will understate true demand for green electricity from households in the Western Cape.

4.1.2: Sample Size

A key requirement for producing reliable valuation estimates using contingent valuation is adequate sample size. Larger samples provide more precise estimates of WTP and covariate relationships, and reduce the likelihood of sampling bias. Given the desirability of larger samples, the choice of sample size is thus a trade-off between the cost of the study and the precision of its estimates (Bateman *et al.*, 2002). Following

Oliver (2009), 400 respondent households was targeted as the minimum sample size, though efforts were made to attain the largest sample possible during the survey administration period.

4.1.3: Survey Administration

Administration of the survey was conducted at the two largest traffic licensing centres in Cape Town over fifteen days in April and May of 2012. Though the use of public service centres as administration venues for contingent valuation surveys is unusual, these centres were extremely well suited to the requirements of this study.

South African motorists are required to replace their drivers' license cards whenever they are stolen or lost, or once every five years on their expiry. When replacing their licenses, people are required to be physically present at the traffic centres to complete an eye-test. These centres could thus be expected to reliably attract a random sample of the population that they serve. Given their status as motorists, the individuals served by these traffic centres are unlikely to be members of low-income households. Thus, it could be reasonably expected that, over multiple days, the queue at these centres should provide an asymptotically representative sample of the upper-middle income population of the Western Cape.

Further, replacing or issuing a driver's license typically involves a long and often boring wait at the traffic centre. This provides an excellent opportunity for survey administration. Waiting in a queue affords people the opportunity to participate the in the survey without being diverted from their planned activities. This should result in higher response rates and smaller participation biases than are typically encountered in public intercept-sampling. Further, by removing distractions and time constraints, the queue environment is likely to improve respondent attentiveness – an invaluable benefit, given the long and somewhat technical nature of most contingent valuation surveys.

4.1.4: Survey Mode

As discussed in Section 2.4, researchers conducting contingent valuation studies face a number of trade-offs in choosing the administration mode for their survey. Face-to-face interviews, mail surveys, and telephonic surveys each have their own strengths and weaknesses, which must be considered in selecting the survey mode most appropriate for application to their experiment.

This study uses a printed survey, which is introduced by an administrator, filled in by the respondent without assistance, and collected on site. This approach combines the ease, low cost, and process standardisation of mail surveys with many of the desirable attributes of face-to-face interviews.

Operating from a desk situated near the entrance of the traffic centre, administrators approached members of the public as they waited in the queue, introduced themselves as researchers, and enquired about their status as bill-payers within their household. Bill-paying individuals were then invited to participate in a quick survey "about electricity" being run by the School of Economics at the University of Cape Town. Respondents who agreed to participate were provided with a survey booklet, along with a clipboard, laminated information sheet and pen with which to complete it. Completed surveys were collected by the survey administrators, or could be deposited in a marked box at the exit.

Administering the survey in this fashion has numerous advantages over both face-to-face interviews and postal surveys. Locating the survey within the context of a personal interaction makes the process of survey completion observable, and will likely lead to increased participation rates. Selection and avidity biases are also reduced by making participation in the survey less reliant on the internal motivation of respondents to complete and return the survey than an equivalent postal survey would. Similarly, reducing the role of the researcher to that of a facilitator rather than an interviewer is expected to reduce interviewer effects and social desirability bias. Respondents are expected to feel more comfortable writing down 'unpopular' opinions than verbally expressing them. The desire to please the interviewer by providing the 'correct' answers is likely to be weaker when filling out an anonymous questionnaire than when conversing personally. As a result, the self-selection and interviewer biases typical of mail and face-to-face surveys are expected to be greatly reduced in this format.

4.1.5: Debriefing

Upon collection of their completed survey booklets, respondents were given a debriefing slip that thanked them for participating, and informed them that the green electricity products described in the survey were hypothetical. Each debriefing slip was marked with a unique identification code corresponding to the number of their survey booklet. Respondents were explicitly informed of their right to withdraw their data at any time by texting this identification code to a specified number, however, no respondents chose to exercise this right. Survey respondents were not paid or compensated for their participation in any way. The debriefing slip can be found in Appendix C.

4.2: Survey Design

This section discusses the survey instrument utilized by this study. The structure of the survey is examined, followed by an explanation of the hypothetical market scenario.

4.2.1: Survey Structure

The survey booklet used by this study can be found in Appendix A. The survey begins with a concise explanation of the need for new power plants, and the choice between coal-burning plants and renewable energy technologies.

This is followed by Section 1 of the survey, which gathers data regarding respondent attitudes and beliefs related to climate change, the environment, and electricity. During survey testing, some respondents indicated that they found these items to be enjoyable and engaging, and their inclusion at the start of the survey is intended to minimize the number of respondents who change their mind about participating early in the survey. Following on from this, Section 2 of the survey gathers data related to the socio-economic and behavioral characteristics of respondent households. At the end of Section 2, respondents are instructed to carefully read the information sheet provided to them, which explains the Province's 15% green electricity target, and outlines the benefits that would be attained if it were achieved. The survey concludes with Section 3, which presents the hypothetical market for green electricity products. This section gathers responses provided to the valuation item, as well as estimates of respondent confidence in their 'yes' responses, and the reasons behind 'no' responses.

The order of presentation used is very similar to that suggested by Carson & Hanemann (2005), differing only in that they recommend items gathering socio-economic data be included as the final section of the survey. Though this was considered, it was decided that such a layout would likely result in higher item non-response rates for these questions.

4.2.2: Information presented to respondents

The hypothetical market scenario presented to respondents in this study is based on the Western Cape Provincial Government's target of producing 15% of all electricity used in the province from renewable sources by 2014, as proposed in the White Paper on Sustainable Energy (Western Cape Provincial Government, 2010). The target is stated as follows:

> "*15% of the electricity consumed in the Western Cape will come from renewable energy sources in 2014, measured against the 2004 consumption baseline of 63.61 million GJ*" (Western Cape Provincial Government, 2010, p.70)

The laminated information page provided to respondents in the course of the survey can be found in Appendix B. This section discusses the information provided to respondents in the course of the study, explaining the relevance of each piece of information, and, where applicable, its derivation from data supplied by the White Paper on Sustainable Energy (Western Cape Provincial Government, 2010).

Electricity Produced

The 15% green electricity target uses 2004 electricity production as its baseline. In 2004, the Western Cape Province consumed a total of 63.61million GJ of electricity. Thus, achieving the target requires the generation of 9.45million GJ of green electricity annually by 2014. A standard conversion (1GWh = 3600GJ) shows this to be equivalent to 2650GWh, or 2 650 000 000 electricity meter units (1 unit = 1 kWh) (Western Cape Provincial Government, 2010).

When described using technical units like GJ, kWh, or MWh, information related to electricity use and production is meaningless to most respondents (Gerpott & Mahmudova, 2011). This was confirmed during pilot runs of the survey, where the respondents were near-unanimous in their selection of the 'Don't know' option when presented with an (ultimately excluded) item asking them to estimate their monthly consumption in kWh. Thus, to facilitate a better understanding of the magnitudes involved, it was decided that the targeted level of green-electricity production should also be presented in terms of the number of average households that could be supplied, which is considered to be more accessible to respondents

Households Supplied

Data from the White Paper on Sustainable Energy (Western Cape Provincial Government, 2010) indicates that households account for around 8% (19 800 000GJ) of the energy consumed in the Western Cape, and electricity accounts for 90.6% of household energy use. Thus, households in the Western Cape consume around 18 million GJ, or 4988GWh of electricity per year – around 28% of the total electricity consumption in the province. Dividing this total amongst the 975 892 electrified households in the province gives an average annual electricity consumption of 5111 KWh per household. The 2650GWh of green electricity that would be produced annually if the 15% target were met is thus enough to supply the annual electricity needs of 518 459 average Western Cape households.

Wind-farm Capacity Required

The plan of action for attaining the 15% green electricity target presented by the Western Cape Provincial Government (2010) indicates that a total of 832MW of green electricity generation capacity would be required. The renewables portfolio presented in this plan is dominated by wind power, which accounts for 680MW (82%) of the required capacity, with the remainder composed mostly of solar photovoltaics (100MW, or roughly 12%), and minor contributions from ocean energy, biomass, hydro-power, and landfill gas, each of which accounts for less than 2%. An early version of the survey attempted to include this breakdown in the valuation scenario, but the resulting description was considered too complex and confusing. Moreover, discussion revealed that some respondents were completely unfamiliar with less well-known technologies such as biomass and ocean energy.

Thus, for convenience and simplicity, the scenario presented to respondents indicates that the full 2650GWh of green electricity required for attaining the target would be supplied exclusively from 832MW of wind-power. Simplifying the portfolio of renewable energy technologies in this manner is expected to improve respondent attentiveness and understanding, without biasing their responses. The 832MW required is equivalent to exactly 160 times the capacity of the Darling wind farm (5.2MW), which at the time of administration was the largest wind-farm, and the only commercial producer of green-electricity in South Africa.

Environmental Benefits

The table of useful figures included in the White Paper on Sustainable Energy (Western Cape Provincial Government, 2010, p.5) indicates that generating 1kWh of electricity from the existing generation-mix requires 1,26 litres of water and 0.529 kg of coal, and results in emissions of 0.936 kg of CO_2. Generating electricity from wind turbines requires no fuel or water inputs, and results in no emissions. Thus, these figures indicate that the targeted production of 2650GWh of green electricity would result in annual savings of:

- 3,3 billion litres of fresh water
- 1,4 million tons of coal
- 2.48 million tons of CO_2

Quantities of this magnitude are often difficult for respondents to conceptualise. Thus, to aid respondent understanding the coal and water savings are presented both as numbers, and in terms of alternative units that respondents may find more familiar and easier to imagine. The chosen units were 100-ton hoppers used to transport coal by rail, and standard-sized Olympic swimming pools. The provision of visual aids and use of alternative units to express technical information is common practice in contingent valuation studies (Carson & Hanemann, 2005; Arrow *et al*, 1993; Schlapfer, 2008).

These benefits are presented as annual rates, rather than cumulative savings over the anticipated 20 year life of the turbines, as this is considered more relevant to the choice facing a respondent who is considering signing up.

4.2.3: The Hypothetical Green-Electricity Market

Choosing an Elicitation Format

Maintaining the realism of hypothetical green electricity market was a key consideration in selecting the elicitation format for this study. To limit hypothetical bias, the fictional green electricity products are presented to respondents as real products on the verge of launching. As such, elicitation formats that imply uncertainty or doubt regarding the price of these goods were considered unsuitable. Experience with contingent valuation studies has shown that respondents often find valuation items using open-ended bids or payment cards confusing and unrealistic; real markets seldom ask them to name their price, or to select their preferred price from a list of suggested values. Where hypothetical market scenarios afford them this ability, respondents are likely to consider these scenarios less believable/realistic, and may even regard them as purely hypothetical exercises (Carson & Groves, 2007). By adopting a form that is familiar, believable and easily understood, hypothetical markets using dichotomous choice elicitation formats are likely to provide truer estimates of respondent WTP (Loomis *et al*, 1996; Hanemann *et al*, 1991). This format emulates the familiar binary choice presented by most product markets; respondents are offered the chance to sign up for the green electricity product at a stated bid price, and must then choose between accepting the offer by signing up, or declining the offer and remaining on the standard tariff package. This study employs a double-bounded dichotomous choice elicitation format.

In order to obtain estimates of the demand for green electricity products that approximate those that a real market would produce, it is critically important that the hypothetical market employed by the study should resemble the likely form of the prospective green electricity market as closely as possible (Carson & Hanemann, 2005). The hypothetical green electricity goods developed for this study are thus loosely based on green electricity products available for sale in foreign electricity markets, as well as the pilot certificate trading system through which the City of Cape Town sells the output from the Darling wind farm (Bird, Wusthagen & Aabakken, 2002; City of Cape Town, 2010).

What would the real Western Cape green electricity market look like?

If the green electricity target were achieved, it is considered likely that the sale of the electricity produced will be conducted on a voluntary basis through a Tradable Renewable Energy Certificate market. The City of Cape Town already operates a small-scale pilot certificate system, through which it sells the output from the Darling wind farm to businesses consumers seeking to bolster their environmental credentials. These certificates are sold in blocks of 1MWh at a price of R250; this equates to a cost of 25c per kWh 'unit', or around 25% of the retail electricity tariff (R1.0637/kWh) paid by most upper-middle income households (Brick & Visser, 2009; City of Cape Town, 2012).

The creation of a renewable energy certificate market facilitates trade in environmental goods; purchasing a 1MWh block of certificates implies the acquisition of ownership rights to the environmental benefits produced by using 1MWh of green electricity. Thus, these certificate systems allow the sale of green electricity to be conducted through two separate markets (Sovakool, 2011; Levin, Thomas & Lee, 2011). Green electricity generators sell the electricity output produced by their plants to Eskom, who distribute it to customers through the existing source-indifferent electricity market. A regulatory agency tasked with maintaining the certificates market then issues the green electricity generator with tradable green electricity certificates for each verified unit of green electricity produced. These certificates give power producers operating renewable technologies the opportunity to sell their output directly into the national grid, whilst the environmental benefits arising from the use of green electricity are traded on a separate market for certificates (Brick & Visser, 2009; Winkler, 2005). Thus, even though the actual electricity supplied to adopting households does not come from the wind farm, their purchase of 1MWh of certificates ensures the supply of 1MWh of green electricity into the grid, where it replaces 1MWh of electricity generated from coal. This system of 'proxy' consumption achieves environmental benefits identical to those of a direct-supply arrangement without requiring the enormous expense of creating separate transmission grids, and spares consumers the inconvenience of supply intermittency (Brick & Visser, 2009; Sovakool, 2011; Levin *et al.,* 2011).

Considering its complexity, it seems unlikely that such a tradable certificates system would operate at a retail level, selling certificates directly to households. It is far more likely that certificates would be repackages into more accessible intermediate green electricity products which would be sold to consumers. The valuation item employed by this study thus makes use of a hypothetical market trading in a range of fictional green electricity products of this type.

'Green Power!©', 'Green Power! Plus©' and *'Green Power! Lite'*©

Section C of the survey contains the hypothetical market items from which WTP data is gathered. This section presents respondents with a description of a range of fictional certificate-based green electricity products, and enquires about their willingness to sign up for the program at a stated price. The hypothetical products developed for this study are called the *'Green Power©!'* packages.

These products offer respondents the opportunity to have a stated quantity of their household's monthly electricity consumption supplied from renewable sources in return for a fixed monthly payment. The cost of these products was given as an absolute value, as this simplifies the decision-making process for respondents, and avoids potential pitfalls involved with expressing prices as an increase in monthly spending or higher cost per unit consumed.

A major concern when using the double-bounded format is that the unexpected presentation of the follow-up item may encourage perceptions that the actual cost of the good is still uncertain, thus inviting strategic responses, or may cast doubt on the believability of the valuation scenario (Carson & Groves, 2007; Loomis *et al*, 1995). This is especially the case where the initial and follow-up items offer identical products at different prices. Thus, to avoid these problems, the initial, higher follow-up and lower follow-up valuation items are presented using three different fictional green electricity products, each of which implies a different monthly contribution towards the attainment of the 15% green electricity target.

Green Power!© is a green electricity tariff package which is described and presented to respondents in the initial dichotomous choice item. Depending on the version of the survey presented, the costs of this package is R100 or R150 per month. For a specified monthly fee, households who sign up will have a stated quantity of their monthly electricity consumption supplied from wind farms.

Depending on their response to the *Green Power!* package, respondents are then offered either the *Green Power! Plus* package, or the *Green Power! Lite* package.

Respondents who indicate their intention to sign up for *Green Power!* are presented with a higher follow-up bid in the form of the *Green Power! Plus*. This product is presented as a premium alternative to *Green Power!* that is specifically targeted at those consumers who are "looking to take their commitment to environmentally-sensitive living to the next level". This package supplies a larger quantity of green electricity at a proportionally higher monthly price than *Green Power!*

Respondents who indicate that they would not sign up for *Green Power!* are offered an alternative in the form of *Green Power! Lite*. This package is targeted at "cost-conscious green consumers who want to do their part to protect the environment without breaking the bank". Households adopting this package essentially agree to purchase a smaller quantity of green electricity at a proportionally lower monthly cost than was offered by the *Green Power!* package.

The quantity of green electricity provided at each payment level for each product is calculated using the current certificate price of 25c per kWh. Although they are not presented as such, these packages are the equivalent of a 'subscription' that purchases a given number of green electricity certificates per month. The technical details of the provision arrangements were considered too confusing and complex to include in the survey. In place of such a detailed description, the survey informed respondents that switching over to *Green Power!* requires no physical change to their electricity connection, and assured them that the security and reliability of their electricity supply will not be compromised.

<u>Payment Vehicle</u>

The payment mode for *Green Power* subscribers depends on the manner in which their electricity payment is made. Whilst many Western Cape households continue to pay for their electricity through a monthly bill, there has been a shift towards the use of pre-paid electricity meters in the province over the past 15 years, largely as a result of initiatives introduced by the City of Cape Town (Western Cape Provincial Government, 2010).

Where households receive a monthly electricity bill, payments for *Green Power!* are made through flat-rate increases in these bills. Green electricity products sold in existing markets around the world frequently use utility bill increases as a mode of payment (Bird *et al*, 2002; Ozaki, 2010; Rundle-Thielle *et al*., 2008). As discussed in Section 3.1, the use of increased utility bills as a mode of payment is also popular amongst contingent valuation studies for all manner of public goods (Hanley & Spash, 1993; Carson & Hanemann, 2005).

Households who use pre-paid electricity meters do not receive monthly accounts, but rather purchase electricity vouchers at retail outlets, which are loaded onto their meters. Whilst they would still pay the monthly fee through their electricity spending, the scenario presented to respondents specifies that the charge will be spread over the first 200 units consumed in each month, so as to avoid the inconvenience of sharp changes in meter balances.

Though payment vehicles that specify prices as a proportional increase in electricity prices were considered, a flat-rate payment vehicle was considered a superior option for two reasons. Firstly, electricity is a low-involvement purchase for many people; respondents may have only a vague idea of what their household spends on electricity each month, and may thus be genuinely unsure of the magnitude of the monthly payment implied by a proportional increase of given magnitude (Gerpott & Mahmudova, 2011; Akai & Nomura, 2004). This concern is particularly relevant to this study, as the price of electricity supplied to Western Cape households has been subject to annual increases of around 30% for the past 2 years. Thus, if respondent WTP was measured as a fraction of existing electricity spending, then the validity of the valuation estimates produced by the study will depend largely on the accuracy with which such spending can be reported. Secondly, even where respondents can accurately state their average monthly electricity spending at current tariffs and express their WTP as a fraction of this, further price increases in June/July 2012 and subsequent years complicate matters. The correct approach to interpreting WTP responses in hypothetical markets using proportionally-specified prices following such a change is unclear. Thus, it was decided that prices should be specified as flat-rate monthly fees.

Customer Protections

Some respondents are likely to display some aversion to these packages on account of their being provided by the public sector. Mistrust of governments is widespread, and where respondents suspect that payments may be squandered or diverted to other uses, this can introduce an element of bias to the valuation-item responses. In order to reduce this effect, the survey sought to reassure respondents that the collected funds would be well managed and used for their intended purpose. The survey thus makes a point of stating that the funds collected from *Green Power!* subscriptions go into a dedicated green electricity fund, and are not mixed with contributed to general public coffers. The accounts for this hypothetical fund are published for public scrutiny, and are subject to annual audits. The funds paid into this account can be used only for the purpose of purchasing green electricity from producers in the Western Cape.

Chapter Five: Estimating WTP

Modelling Double-Bounded Dichotomous Choice Responses

This chapter explains the theoretic conception of the valuation exercise, and outlines the approaches taken in econometric modelling. The chapter is composed of four major parts. Section 5.1 examines the utility-theoretic framework within which the study operates. Section 5.2 examines the link between the responses elicited by hypothetical markets using dichotomous-choice items and respondent WTP. Two rival interpretations of these responses are examined. Section 5.3 examines the various approaches commonly taken in valuation studies employing the double-bounded dichotomous choice elicitation format.

5.1: Theoretical Conception of the valuation exercise

This study operates within the standard economic conception of consumers as self-interested utility-maximizing agents with fully developed preferences over all available goods. The theoretical basis of the study presented here is adapted from the models presented by Boman, Bosted & Kriström (1999); Cameron & Quiggin (1994), Carson & Hanemann (2005), Hanemann (1984), and Hanemann & Kanninen (1998).

Where q is a variable that represents the quantity of electricity of green electricity consumed, and z is a vector representing all other goods available to the consumer, the individual consumer's utility function is expressed as:

$$u(z, q) \qquad (1)$$

Or as the equivalent indirect utility function:

$$v(p, q, y) \qquad (2)$$

Where p is a price vector for all goods, and y denotes disposable income.

Individual utility is assumed to be strictly increasing and quasi-concave in q, such that changes in price and income have their standard effects on utility. No assumption of quasi-concavity in q is made, but individual utility is assumed to be strictly non-decreasing in q.

The hypothetical market scenario developed for this study is based on the Western Cape Provincial Government's 15% green electricity target as outlined in the 2010 White Paper on sustainable energy (Western Cape Provincial Government, 2010).

The attainment of the green electricity target is denoted as a shift from q^0 to q^1, where q^0 is the status-quo consumption of green electricity, and q^1 represents the quantity of green electricity that would be consumed if the targeted 2650GWh of green electricity per year is achieved. The hypothetical market offers the respondent an opportunity to purchase this change (or a portion thereof) by signing their household up for a green electricity product at a stated monthly subscription fee. Within this utility-theoretic framework, the effect of achieving the shift from q^0 to q^1 is seen in the resulting shift in utility from u^0 to u^1, where:

$$u^0 \equiv v(p, q^0, y) \quad \text{and} \quad u^1 \equiv v(p, q^1, y) \qquad (3)$$

Given the public-good nature of the benefits produced, increasing the amount of green electricity consumed from q^0 to q^1, produces utility gains of $(u^1 - u^0)$ for all consumers. The appropriate measure of the monetary value of this utility change is the Hicksian Compensating Variation, C. In terms of (3), C is defined as:

$$v(p, q^1, y - C) = v(p, q^0, y) \qquad (4)$$

That is to say, C is equal to the value of the maximum payment that an individual would be willing to make in order to secure the attainment of the 15% green electricity target. This is generally referred to as their maximum 'willingness to pay' (WTP) for the change from q^0 to q^1.

$$WTP(q^0, q^1, p, y) = C(q^0, q^1, p, y) \qquad (5)$$

The utility change produced by the shift from q^0 to q^1 can also be expressed in terms of household expenditure functions. Given that the expenditure functions corresponding to the utility functions *u(z, q)* and *v(p, q, y)* is *y = m (p, q, u)*, C can be defined as follows:

$$C = m(p, q^0, u^0) - m(p, q^1, u^0) \tag{5'}$$

$$= y - m(p, q^1, u^0) \tag{5''}$$

That is, C is equal to the difference between expenditure required to achieve utility u^0 under the status quo, and the expenditure that would be required to achieve that same utility once the use of green electricity had attained the targeted increase from q^0 to q^1. Thus, assuming that utility is increasing in (or indifferent to) q, attainment of the 15% green electricity target will produce non-negative changes in utility for all consumers. From this it follows that $m(p, q^0, u^0) \geq m(p, q^1, u^0)$, as utility u^0 can be maintained with equal or lower levels of expenditure once the green electricity target has been obtained.

Given the utility function u(z, q), recall that *z* denotes vector of all other goods available to the consumer, some of which are presumably to be essential. Expenditure on these goods must account for some non-zero portion of incomes, as not even the most passionate environmentalist can survive on green electricity alone. Thus, C is necessarily less than income. Further, the assumption that utility is non-decreasing in q implies that household WTP for the shift from q^0 to q^1 is non-negative. This is intuitively reasonable, since household WTP for premium-priced green electricity is based on their demand for non-use components of value, like the environmental benefits it produces. Whilst some consumers are sure to have a WTP of zero for these benefits, it is difficult to conceive of a situation in which a consumer would actually make payments to prevent the increased use of green electricity, so long as adoption is voluntary and security of supply remains uncompromised. The essential nature of the goods in vector z, and the non-negativity of WTP impose restrictions on C that define the upper and lower bounds of its possible values.

$$C < y \qquad \text{and} \qquad C \geq 0 \tag{6}$$

This utility-theoretic conception provides a broad framework within which the responses gathered by the dichotomous-choice based hypothetical market can be interpreted and modelled.

5.2: Interpreting discrete-choice responses in this framework

5.2.1: The WTP-interval interpretation

As noted in Section 2.4.3, the dichotomous-choice elicitation format is regarded to be more realistic than most others. However, this realism comes at a cost – dichotomous-choice items provide a rather limited measure of respondent WTP. Responses to dichotomous choice valuation items do not provide direct measures of WTP, but rather define the bounds of a range within which WTP must lie.

When presented with an item proposing some good or program that will produce the change from q^0 to q^1 at a bid price of B, a rational agent will agree will accept the offer and purchase the good only if the transaction produces net gains to their utility. That is, only where the bid value, A, is less than or equal to their maximum WTP for the good. Using the notation developed above:

$$\Pr(\text{'yes'}) = \Pr(\text{WTP} \geq B) \tag{7}$$

And, given that C is equal to WTP:

$$\Pr(\text{'yes'}) = \Pr(C(q^1, p, y) \geq B) \tag{7'}$$

Thus, under this interpretation, the responses gathered by a dichotomous-choice style hypothetical market define the bid values presented to respondents as upper or lower bounds on the range of possible WTP values. Thus, a statistical model that estimates the probability of a 'yes' response as a function of the bid level and relevant respondent characteristics can be used to estimate the WTP distribution, and to obtain a representative estimate of respondent WTP that can be used for aggregation.

5.2.2: The Minimum Legal WTP interpretation

An alternative interpretation of dichotomous-choice responses is offered by Harrison & Kriström (1995). They argue that the appropriate interpretation of an individual's response to a dichotomous-choice item in a hypothetical market is as an implied contract between the interviewer and the respondent. The importance attached to the realism and credibility of the hypothetical market scenario and the sincerity of responses both lend support to this interpretation. Harrison and Kriström (1995) argue that the WTP-interval interpretation of responses violates this implied contract. A respondent who agrees to sign up for a green electricity product at a price of, say, R150 per month, has only agreed to pay that stated amount. Whilst larger payments could potentially be extracted from them to assign them any WTP value in excess of the agreed amount is a direct breach of the contract implied by the hypothetical market. The contractual interpretation of responses underlies the non-parametric 'Minimum Legal WTP' models estimated in this study.

<u>5.2.3: Are hypothetical market responses a reliable proxy for real behaviour?</u>

That contingent valuation estimates tend to overstate real economic commitments is widely noted. This result is remarkably robust, and has been shown to hold true for private as well as public goods (Arrow *et al*, 1993; Carson & Hanemann, 2005; Carson & Groves, 2007; Byrnes *et al.,* 1995; Diamond & Hausman, 1994). This discrepancy appears to be present in studies examining demand for green electricity products. Whilst contingent valuation studies frequently suggest participation/adoption rates of 40-70%, premium-priced green electricity products seldom experience real-world adoption rates over 2% (Bird *et al.*, 2002; Diaz-Rainey & Tzavara, 2009; Byrnes *et al*., 1999; Either, *et al*., 2000; Akai & Nomura, 2004).

Perhaps the most compelling explanation of this discrepancy holds that respondents may be answering a question that is subtly different from that which is being asked. Rather than indicating their intention to immediately purchase the proposed good, their agreement may indicate their favourable view of the product, and/or their assessment of the price as being fair or reasonable (Diamond & Hausman, 1994). Thus, by saying 'yes', respondents would be indicating that they *would* be willing to pay the specified price, *if* they were in the market for such a good, or *if* they were freed of their usual budgetary constraints (Loomis *et al*., 1995). Though care can be taken to remind respondents of their budget constraints, the existence of substitute goods/causes, and the intended meaning of the elicitation item, it is extremely difficult to assess the sincerity of 'yes' responses as an indication of a real intention to part with money.

Humans are also notoriously poor predictors of their own behaviour, especially for actions that are regarded to be somehow virtuous, and actions that require some form of immediate personal sacrifice for long-term gains (Ariely, 2008). This inability to accurately predict behaviour is evident in countless aspects of life; gym membership use, diet plans, retirement saving, commitment to monogamy, and New Year resolutions, to name a few. Thus, though respondents may be indicating a genuine intention to purchase the good, this intention may not translate into real behaviour (Oliver, 2009).

Finally, this divergence may arise from genuine uncertainty. Environmental goods like green electricity are novel products which are unfamiliar to respondents; a lack of relevant experience and knowledge could leave respondents genuinely uncertain of their likely actions (Poe, & Welsh, 1995; Zarnikau, 2003).

5.2.4: Calibration of responses

It is highly likely that the raw dichotomous choice response data will include a number of "yes" responses that do not represent credible commitments to purchase the product. To identify these bids, and to moderate their effects on WTP estimates, the response data was calibrated using an approach adapted from those employed by Ethier *et al.* (2000), Li and Mattson (1995), and Champ, Bishop, Brown & McCollum (1995). Immediately after each WTP item, respondents who accepted the offered program at the proposed price were presented with a percentage scale, and asked: *"If you answered 'Yes', how sure are you that you would actually sign up?"* The inclusion of this item allows respondents to disclose their uncertainty regarding their actual behaviour, and creates space for respondents who feel awkward about selecting the undesirable 'no' option a chance to reveal their honest preferences.

The certainty values provided by respondents were used to calibrate the response data. Response-calibration alters the response data by recoding 'yes' responses with attached certainty estimates below a chosen threshold value as 'no' responses (Li & Mattson, 1995). Ethier *et al*. (2000) found that response-calibration of this type substantially reduces the discrepancy between contingent valuation results and outcomes observed in the real world. This is intuitively sensible; if contingent valuation studies consistently overstate real WTP, then it follows that some of the 'yes' responses provided in the hypothetical market are not credible. Where respondents indicate substantially different estimates of the likelihood of their actually purchasing the good, it is clearly inappropriate to regard their 'yes' responses as equivalent. Calibrating responses in this fashion facilitates the self-identification of respondents providing insincere 'yes' responses. Further, calibration will reduce mean WTP estimates, in line with the much-cited principle of 'conservative bias' (Arrow *et al*, 1993).

Alternatively, the data gathered from certainty measures can be used for post-estimation calibration; this approach is discussed in Section 6.2.

5.3: Econometric Models

The econometric models for estimating WTP from dichotomous choice response data can be broadly divided into two major classes; parametric and non-parametric. This section explains the approach taken to estimation, and describes the econometric models used in estimating the WTP distribution.

5.3.1: Non-parametric models

Non-parametric approaches require no assumptions regarding the nature of the WTP distribution underlying the survey responses, as they impose no structure across the different bid levels (Vossler, 2003). Though they may require larger samples to attain an estimate of given precision than their parametric cousins, the validity of the estimates produced is not dependent on distributional assumptions – an especially desirable attribute, considering how limited existing knowledge of household WTP for green electricity is (Harrison & Kriström, 1995; Boman *et al*, 1999; Seung-Hoon & Su-Yoon, 2009). Moreover, non-parametric techniques provide an elegant method for estimating WTP in a manner that is intuitively appealing, computationally simple and easily understood by non-specialists (Boman *et al*, 1999; Abdullah & Jeanty, 2012).

Non-parametric estimation techniques for dichotomous choice response data are generally based on the survival-time and dose-response models used in medical statistics (Boman *et al.*, 1999; Carson & Hanemann, 2005). These models seek to provide an empirical estimate of the probability that some event of interest will occur during the interval between two successive observation points; for example, the likelihood of a patient's death in specific time intervals following a treatment (Harrison & Kriström 1995; Boman *et al.*, 1999). Applying this model to a dichotomous choice, the bid value is analogous to time, whilst the event of interest is a 'no' response. As the bid value rises, the proportion of respondents who continue to accept the offer is expected to decline (Harrison & Kriström, 1995; Vossler, 2003).

The non-parametric model employed by this study is designed to produce a highly conservative lower-bound estimate of mean WTP. This model is an extension of the single-bounded model developed by Harrison & Kriström (1995) to the double-bounded case. Non-parametric models estimated by this study are based on the 'Minimum Legal WTP' interpretation of the contingent valuation response data at each bid level discussed in Section 6.1. This interpretation holds the acceptance of the good at the bid price to define a contract between the interviewer and the respondent. Each respondent is thus assigned a WTP value exactly equal to the highest bid value to which they agreed. This corresponds with the lower bound of the interval implied by the WTP-interval approach (Harrison & Kriström, 1995).

Returning to the conception of the Hicksian compensating variation C presented in Section 5.1, an individual's WTP can be given in terms of expenditure functions as follows:

$$\text{WTP} = C = m(q^0, u^1) - m(q^1, u^1) = \int_{q0}^{q1} \frac{\partial m}{\partial q} . dq \qquad (8)$$

The proposed lower-bound measure is thus equal to the area under this curve. That is:

$$C = \frac{\partial m(q^1, u^1)}{\partial q} (q^0 - q^1) \qquad (9)$$

Graphically this can be represented as shown in Figure 5.1.

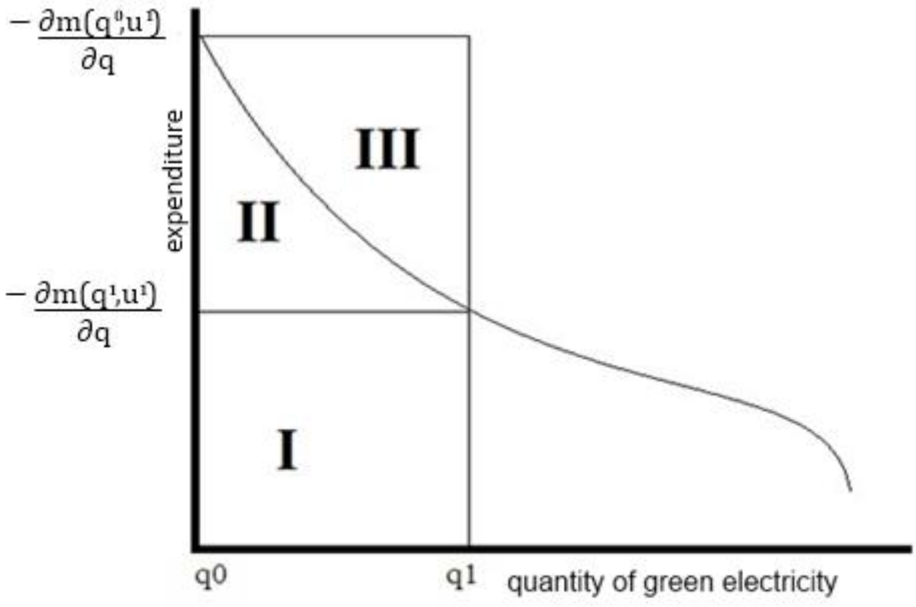


__Figure 5.1:__ **Graphical representation of the minimum-legal WTP measure.**

The hypothetical marginal WTP curve shown in Figure 5.1 represents the utility gains produced by an increase in the use of green electricity from q^0 to q^1. The true measure of welfare produced by this change is equal to the area (I+II). However, dichotomous choice elicitation items allow researchers to observe this function only at discrete points that correspond to the chosen bid values. Thus, the assumptions made regarding the behaviour of this curve between successive bid-points are an important determinant of the WTP estimates produced. The non-parametric model used by this study seeks to establish a lower-bound estimate of mean WTP by adopting the most conservative assumptions in interpreting the response data. In terms of Figure 5.1, this lower-bound measure is equivalent to the area I.

The mean WTP measure produced by this model corresponds closely with the Laspyres measure presented by Boman *et al.* (1999). The primary difference between these models is the treatment of the data where the observed rates of bid-acceptance do not decline across increasing bid values as expected. To compute the Laspyres measure, responses from adjacent bids that violate the monotonic-decline rule must be pooled, and included as a single broader category. The approach taken in computing the minimum-legal WTP model used in this study eschews this approach, opting to include the responses without such alterations.

5.3.2: Parametric Models

Parametric models estimate WTP by assuming particular properties of the population distribution, and then approximating this distribution by using regression analysis to evaluate a limited number of parameters. More formally: the researcher wants to know $\Pr(j|x_i)$, that is, the probability of a binary outcome, given a vector of respondent and scenario characteristics. Since this probability cannot be directly observed, the, parametric approaches begin from the assumption that $\Pr(j|x_i) = P(j|x_i, \theta)$, where P is a known function with a vector of parameters Θ. Here, $\theta \in \Theta$, where Θ is a finite parameter space. Thus, researchers can obtain the desired estimate $\Pr(j|x_i)$ by estimating θ from a sample of the relevant population (Abdullah, 2009).

Unlike their non-parametric cousins, parametric models allow for the inclusion of covariates as explanatory variables. Comparing the nature and strength of the estimated WTP-covariate relationships with those suggested by economic theory provides a useful measure of construct validity for the study. The multivariate models produced by parametric techniques are also of particular value for extrapolating estimates from the survey sample to the general population where these differ in some systematic fashion (Hanley & Spash, 1993; Carson & Hanemann, 2005; Abdullah & Jeanty, 2012).

Parametric techniques for extracting WTP estimates from double-bounded dichotomous choice data are generally either binary-response models that estimate the probability of a 'yes' response as a function of bid values and selected covariates, or interval-data models which use WTP intervals defined by bid values and responses as a dependent variable (Balana, Catacutan & Makela, 2012).

Contingent valuation studies employing discrete-choice models typically adopt logit, probit, or bivariate-probit specifications to extract estimates of the latent WTP from dichotomous choice response data (Balana *et al.*, 2012; Abdullah, 2009). Studies employing the interval-data approach typically adopt the canonical discrete choice contingent valuation model developed by Hanemann (1984) and extended to the double-bounded case by Hanemann, Loomis & Kanninen (1991).

The models chosen for use in this study are the single bounded logit and probit models, the bivariate probit model, and the interval-data model.

Single-bounded Models

The classic approach to estimating WTP from dichotomous-choice response data involves the use of a binary-response model, typically the logit or probit (Arrow *et al*, 1993; Harrison & Kriström, 1995; Hanemann *et al.*, 1991). Though the development of more sophisticated approaches for estimation from double-bounded dichotomous choice data has reduced the popularity of single-bounded models, it is still common practice to compare the WTP estimates obtained from a logit model of the responses to the initial bid with those produced by other specifications (Harrison & Kriström, 1995; Carson & Hanemann, 2005).

The single-bounded logit and probit models are estimated using the response data from the initial bid item only. Using single-bounded models to analyse the responses to the follow-up bid is inappropriate, since the value of the second bid presented to each respondent is endogenously determined by their initial response. As a result, the follow-up responses contain a selection bias, and will not conform to traditional Bayesian probability properties (Balana *et al*, 2012). Due to this selection bias, single-bounded models of responses to follow-up bid items will indicate misleadingly high acceptance probabilities for the high follow-up bids presented to respondents who accepted the initial bid, and misleadingly low acceptance probabilities for lower follow-up bid values presented to respondents who rejected the initial bid.

Double-Bounded Models

The choice between rival approaches to WTP estimation using the double-bounded format is informed by the nature of the decision-making process used by respondents. As a matter of convention and convenience, it is often assumed that the responses to both bids are derived from the same known and unchanging WTP value. Without this assumption, the motive for including the follow-up bid is unclear, and the validity of the double-bounded format would be questionable (Harrison & Kriström, 1995; Alberini *et al.,* 1997). However, this assumption is often violated in practice, and indeed, the context and presentation of the follow-up bid differ from those of the initial bid in several ways that make this assumption questionable.

Ultimately, the validity of contingent valuation depends on the assumption that respondents consider the hypothetical market to be credible, and treat the decision as if it were a real purchase (Carson, 2000; Harrison & Kriström, 1995; Alberini *et al.,* 1997; Poe, Welsh & Champ, 1997). Dichotomous choice elicitation formats are considered the most believable, as they simulate the conditions of purchase in most markets. Dichotomous choice items are thus said to be 'incentive compatible' (Arrow *et al*., 1993; Hanemann & Kanninen, 1998; Carson & Groves, 2007). However, the incentive compatibility of single-bounded items does not obviously extend itself to the follow-up bid. Assuming that respondents consider the initial offer to be credible, the unexpected introduction of the follow-up could be considered a betrayal of the agreement, inviting protest bids; as a challenge to the credibility of their first response, inviting yea-saying; or as an indication that prices for the good in question are not yet established, inviting strategic responses. In all of these cases, the responses elicited from follow-up bids will produce biased estimates of WTP (Harrison & Kriström, 1995; Poe *et al.,* 1997).

Even where these biases do not arise, respondents may experience a genuine change in their WTP as a result of 'preference discovery' during the survey process. Considering that the initial bid presented in the hypothetical market is very likely to be their first encounter with green electricity as a product for sale, it is highly plausible that that the experience may inspire some form of preference revision in respondents. Preference discovery is most likely to occur in markets for novel and unfamiliar goods (like green electricity), for which many respondents are likely to have poorly-developed preferences (Alberini *et al*., 1997; Zarnikau, 2003; Carson & Groves, 2007).

Where the WTP distributions estimated from the initial and follow-up bids differ, interval-data models (which assume unchanging WTP) produce biased results and are unreliable. Further, single-bounded models fail to account for preference-discovery effects and make inefficient use of the available data. In these cases, it is appropriate to model both responses simultaneously but separately as a bivariate distribution (Alberini, 1995; Poe *et al.,* 1997).

The Bivariate Probit Model

The bivariate-probit model proposed by Cameron and Quiggin (1994), simultaneously estimates separate distribution parameters for the WTP implied by the initial and follow-up bids, producing two correlated WTP equations, with jointly distributed normal error terms (Areal & Macleod, 2006; Alberini *et al,* 1997). The bivariate probit specification allows comparison of WTP distribution implied by each bid, and facilitates more rigorous interrogation of the relationships between the two WTP estimates and explanatory covariates (Poe *et al.,* 1997; Alberini, 1995). The bivariate normal distribution estimated by this model takes the form

$$R^*_1 = \alpha_1 + \beta_i A_1 + \sum \beta x_i + \varepsilon_1$$

$$R^*_2 = \alpha_2 + \beta_i A_2 + \sum \beta x_i + \varepsilon_2$$

$$\mathrm{corr}[\varepsilon_1, \varepsilon_2] = \rho \qquad (10)$$

Where R_1 and R_2 are the binary WTP responses, A_1 and A_2 are the corresponding first and second bid values, x_i is a vector of respondent characteristics, and the β and α are the coefficients to be estimated. The covariance between the error terms from the estimated equations is denoted ρ. The value of ρ provides a measure of the extent to which R_1 and R_2 are jointly determined – a value of zero would imply no correlation whatsoever between the error terms, and would support the use of a separate single-bounded model for each response, whilst a value of 1 would indicate perfect joint determination, and the bivariate probit model would reduce to the interval-data model of Hanemann *et al.* (1991). Thus, where the value of ρ is close to 1, this indicates support for the use of the interval-data model. For lower ρ values, below 0.7 (Alberini, 1995) or 0.8 (Poe *et al.,* 1997) the bivariate probit is preferred, as the WTP distributions implied by the initial and follow-up responses differ.

Following Abdullah & Jeanty (2011), the mean WTP and 95% confidence intervals are calculated using the approach developed by Krinsky & Robb (1986), sometimes known as the parametric bootstrapping approach. This approach operates by taking a large number of draws (50 000, in this study) from a multivariate normal distribution with means given by the regression coefficients, and covariance given by the estimated covariance matrix of the coefficients (Hole, 2006). A simulated WTP distribution is produced by estimating a WTP value for each draw using the regression equation. By removing the highest and lowest 2.5% of the estimated values, and estimate of the 95% confidence interval for WTP is obtained. The confidence intervals produced in this fashion are commonly referred to as percentile intervals (Poe *et al.,* 1997). Despite its computational intensity, this approach to estimating confidence intervals is considered superior to other bootstrapping methods, as it does not require the assumption of a symmetrical WTP distribution (Hole, 2006).

The predictive power of the bivariate probit model is computed using the approach developed by Kanninen and Khwaja (1995), who propose a measure based on the counts of correctly versus incorrectly classified observations. The standard approach for classifying predictions on binary outcomes is to code those individuals whose predicted probability is 0.5 or greater as positive predictions. However, since double-bounded dichotomous choice response data have four possible outcomes (Yes/Yes, Yes/No, No/Yes, and No/No), this approach is unviable. The analogous 4-category approach - reducing the threshold probability to 0.25 - is also rejected, as numerous respondents could be predicted to belong to more than one category. Instead, Kanninen & Khwaja (1995) propose a method for assessing predictive power that explicitly mirrors the sequential nature of the responses. First, each respondent is classified according to their predicted response to the first bid. The predicted initial response for an individual is considered to be 'yes' if the predicted probability of a 'yes' response exceeds the predicted probability of a 'no' response. That is, if the sum of the predicted probability of their belonging to the Yes/Yes and Yes/No categories is greater than the sum of the predicted probabilities of their belonging to the No/Yes or No/No categories. The proportion of respondents for whom the predicted initial response corresponds with the observed response is known as the 'initially correctly classified count' (ICCC) measure. Applying an analogous procedure to the predicted and observed responses to the second bid for the initially correctly classified respondents produces the 'fully correctly classified count' (FCCC), which measures the predictive power of the model as a whole (Kanninen & Khwaja, 1995)

The bivariate probit distribution can be estimated easily using the 'biprobit' command in Stata 11.

The “Interval Data” Model

An alternative to the bivariate probit, and amongst the most popular of approaches to estimating WTP from double-bounded response data is the model first proposed by Hanemann *et al.* (1991). This model is often referred to as the interval-data, or ‘standard double-bounded’ model. The Hanemann *et al*. (1991) model differs from the bivariate probit model in that it begins from the assumption that responses to the initial and follow-up bids are both based on the same stable and unchanging individual WTP value. Where bivariate probit models produce rho values approaching unity, this indicates joint-determination of the responses to the initial and follow-up bid values, which supports the hypothesis of a stable, known individual WTP (Alberini, 1995; Abdullah & Jeanty, 2012; Poe *et al.,* 1997). However, lower rho values indicate that the process of response determination for the two bids is itself bivariate. Where this is the case interval-data models will produce biased estimates, though this bias is generally small enough to be considered acceptable where rho is greater than 0.7. The Hanemann *et al*. (1991) interval-data model is both theoretically and practically superior to the biprobit model where rho values approach unity (Alberini, 1995; Balana *et al.*, 2012).

The double-bounded dichotomous choice format presents each respondent with two bids, giving rise to four possible outcomes: (yes/yes), (yes/no), (no/yes), and (no/no), the probabilities of which are denoted π^{yy}, π^{yn} , π^{ny} , and π^{nn} . In terms of G_c, the cumulative density function of our stochastic WTP variable, the probability of these outcomes being realised for an individual respondent can be expressed as:

$\dot{P}r$ (Yes/Yes) $\equiv \pi^{yy} = Pr(C \geq A_u) = 1 - G_c(A_u)$

$\dot{P}r$ (Yes/No) $\equiv \pi^{yn} = Pr(A_u \geq C \geq A) = \equiv G_c(A_u) - G_c(A_l)$

$\dot{P}r$ (No/Yes) $\equiv \pi^{ny} = Pr(A \geq C \geq A_l) = G_c(A) - G_c(A_l)$

$\dot{P}r$ (No/No) $\equiv \pi^{nn} = Pr\ (A_l \geq C) = G_c(A_l)$ (11)

The likelihood function for the model is thus:

$$\ln L^D(\theta) = \sum_{i=1}^{N}\{d_i^{yy}\ln\pi^{yy}\left(A_{i,}A_u\right) + d_i^{yn}\ln\pi^{yn}\left(A_{i,}A_u\right) + d_i^{ny}\ln\pi^{ny}\left(A_{i,}A_l\right) + d_i^{nn}\ln\pi^{nn}\left(A_{i,}A_l\right)\} \tag{12}$$

Where d^{yy}, d^{yn}, d^{ny}, d^{nn} are dummy variables for the four response profiles. These take a value of one for respondents falling into their corresponding response profile, and a value of zero for all others. Estimating this function by means of maximum-likelihood using stata 11 is made straightforward by the 'doubleb' command (Lopez-Feldman, 2009).

Chapter Six: Survey Results

Discussion and Analysis of the Data Collected

6.1: Assessing the Survey Process

Over the course of fifteen surveying days, a total of 590 eligible individuals were approached whilst they waited in queues at Cape Town traffic centres. Respondents were considered eligible to participate in the study if they identified themselves as bill-payers in their households. Of these, 464 agreed to participate in the survey. This gives an aggregate response rate of 79.5%, which is quite high relative to those obtained by comparable studies in the literature (see Table 3.3). This response rate and sample size compare favourably with the 74% response rate and 405-respondent sample attained in the 2007-8 telephone survey conducted by Oliver *et al.* (2011) in their study of green electricity demand.

Two factors are speculated to be responsible for these high response rates; the popularity of the topic, and the virtues of the administration venue. Green electricity and environmental issues appear to be very popular and relevant to a large proportion of the sampled population. Further, the traffic centres provided an ideal environment for the administration of a contingent valuation survey, as queuing times in excess of an hour were frequently observed. Respondents were thus interested or bored, and so were unusually eager to participate in the survey.

Informal observations made during the administration of the survey suggested a number of interesting trends, for which future studies may consider gathering data. Most notably, a tendency was observed for the participation choices made by the first few respondents approached to greatly influence those of people approached subsequently. One instance was especially notable in this regard. Upon being approached and asked to participate, and elderly lady protested, loudly shouting "No, No, No! You people bother me so often, just leave me alone" (we had not previously encountered her). Following this outburst, the nine remaining members of the queue were unanimous in their refusal to participate. Another noteworthy observation was the existence of a relatively vocal minority who expressed their scepticism regarding the existence and extent of climate change as a man-made phenomenon.

Of the 464 surveys gathered, 439 were considered fit for use, the remainder being unacceptably incomplete, or containing obviously nonsensical responses, such as uniform selection of the first option for all items, uniform selection of all options for all items, and, in one case, the provision of doodle-drawings and anti-government slogans in lieu of responses.

6.2: Explanatory Variables and Sample Characteristics

This section examines the approach taken in measuring the respondent characteristics that were selected for use as explanatory variables in multivariate models of WTP, and presents a summary of the results obtained. The selection of variables for inclusion as covariates was informed by the literature review presented in Chapter 3, as well as the nature of the actual choices facing South African policymakers.

6.2.1: Demographic Variables

The survey instrument included items that examined the after-tax household income, age, education, and gender of respondents. The results obtained are presented below.

After-Tax Income

Household income data was collected by item B5, which asked respondents to assign their household to one of a series of monthly income brackets increasing in intervals of R10 000. The data collected from this item is shown in Figure 6.1 below. Of the 439 surveys, a response rate of 92.7% (n=407) was achieved, which is high for an item of this type (Rea & Parker, 2005), exceeding our expectations and matching the 93.6% response rate achieved by Oliver *et al*. (2011) in their 2008 study almost exactly.

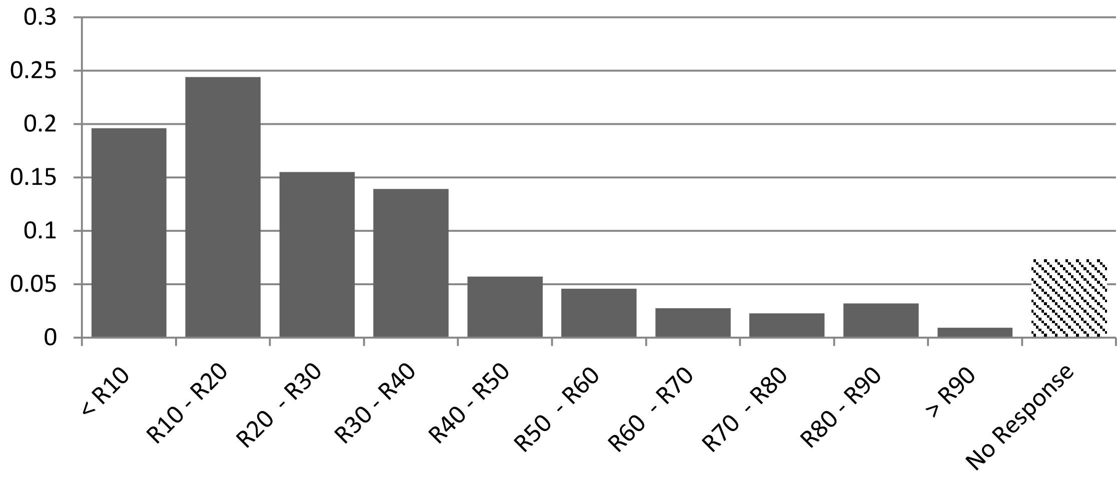


Figure 6.1: Monthly Disposable Household Income in thousands of Rands (n=439)

Both the mean and median income values fall in the R20 000-R30 000/month category. These income figures are consistent with those expected of our target population of upper-middle income Western Cape households.

Respondent Gender and Age

Data related to respondent gender and was gathered using item B1, which simply asked respondents to state their age in years, and to indicate their gender by ticking a box. The response data are summarised in Table 6.1. More than 90% of respondents indicated themselves to be between 20 and 60 years old. The mean age was 39.47 years with a standard deviation of 13.26 years, and the median age was 40. Of the 439 respondents surveyed, 214 (48.75%) were female, 195 (44.4%) were male, and 30 (6.8%) provided no response to the question. The slightly higher proportion of female respondents in the sample corresponds with official population data, which indicates that 52% of Cape Town residents are female (StatsSA, 2012).

Table 6.1: Respondent age and sex (n=409)

	>20	20-29	30-39	40-49	50-59	60-69	70-79	
Male	0.014	0.114	0.110	0.163	0.107	0.030	0.016	0.55
Female	0.023	0.131	0.084	0.105	0.086	0.016	0.00	0.45
Sample	0.037	0.245	0.193	0.268	0.193	0.046	0.016	

Education

Education is measured by item B6, which asks respondents to select a category indicating the highest level of education attained by a member of their household. Though the item itself elicits a categorical response, this is interpreted as a continuous variable corresponding to the minimum number of years taken to attain the indicated qualification in the South African education system. The response frequency and implied number of years of education for each category is presented in Table 6.2.

Table 6.2: Highest Educational Qualification attained by a household member (n=434)

	Incomplete High School	Matric	Other Tertiary	3 Year Degree	Honours Degree	Masters Degree	PhD
Proportion of sample	0.07	0.26	0.12	0.26	0.14	0.12	0.03
Years of education required	10	12	14	15	16	18	21

Applying the transformation shown in Table 6.2, a mean of 14.45 years of education is found, whilst the median is 14 years. Both of these values correspond to the 'other tertiary qualification' category, which includes diplomas, technical qualifications, and other similar qualifications. Slightly less than one third (32%) of respondents indicated their highest qualification to be a matric certificate or less, whilst more than half of the 67% of respondents with tertiary qualifications held university degrees.

Monthly electricity spending

Data for reported monthly household spending on electricity was gathered using item B4. This item asks respondents to indicate their average monthly electricity spending by selecting one of six spending categories. For the purposes of the summary statistics presented here, each respondent household is assigned a value equal to the upper bound of their selected spending bracket.

Of the 439 respondents surveyed, 290 (66%) indicated that their household is supplied with electricity through a prepaid meter, whilst the remaining 149 (34%) received monthly electricity bills. However, a significant difference was observed in the electricity spending reported by each of these groups. Households who receive a monthly bill for their electricity reported a mean value of R808 spent on electricity during a typical summer month. This is 15% higher than the R711 reported by households who purchase their electricity through prepaid meters. The mean monthly electricity spending reported by all respondents was R745, with a standard deviation of R295. The electricity spending data is summarised in Figure 6.2 and Table 6.3, which present the results obtained for monthly-bill and prepaid households, as well as for the aggregated sample. Table 6.3 also presents the results of a t-test assuming unequal variances that confirms the positive relationship between electricity spending and payment by monthly-bill to be significant at 0.1%.

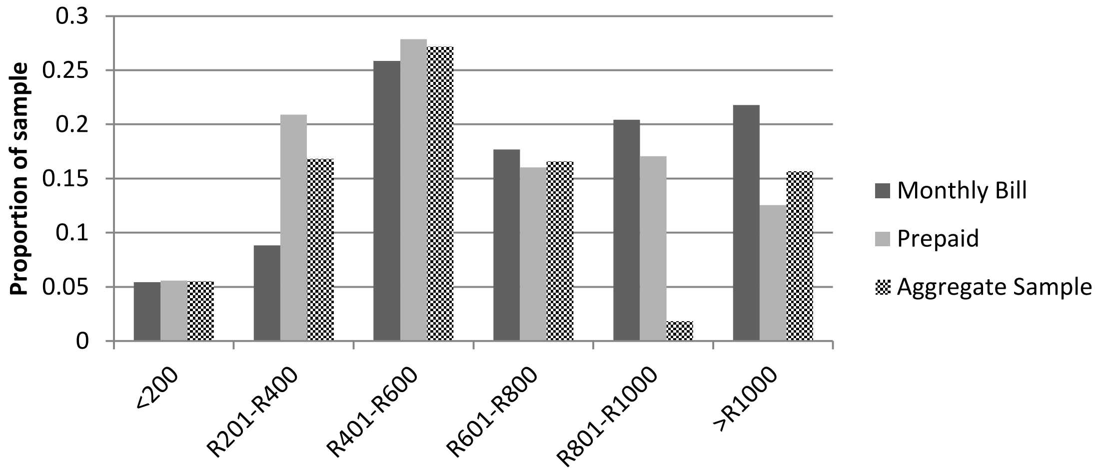


Figure 6.2: Reported household electricity spending in ZAR during an average summer month (n=434)

Table 6.3: Reported electricity spending (R/month) by mode of electricity purchase

	n	Mean	Std. error	95% confidence interval	
Monthly bill	147	R 808.16	24.41	759.92	856.41
Prepaid Meter	287	R 711.49	17.11	677.82	745.18
Combined	434	R 744.24	14.17	716.39	772.09
Difference		R96.67	29.81	37.99	155.34
Ho: diff = 0				t	= 3.2425
Ha: diff < 0	Pr(T<t) =	0.9993		Satterthwaite's Degrees of Freedom	= 289.077
Ha: diff != 0	Pr(T>t) =	0.0013			
Ha: diff > 0	Pr(T>t) =	0.0007			

The finding that households supplied through prepaid meters reported lower electricity spending lends support to the City of Cape Town's claim that prepaid meters help to reduce household electricity consumption. By forging stronger cognitive links between consumption and payment, and providing more detailed feedback on the electricity consumption involved in various activities, prepaid meters are claimed to reduce electricity consumption by 10-12% (City of Cape Town, 2012). Another notable finding is a strong correlation between electricity spending and household income. A test for pairwise correlation between electricity spending and income produces a correlation coefficient of 0.35, significant at all levels.

Since no established measure of the typical electricity spending amongst the wider population of upper-middle income Western Cape households could be found, a measure was computed using data taken from the "State of Energy and Energy Future's Report" (City of Cape Town, 2011), which is shown in Table 6.4 below.

Table 6.4: Deriving a representative measure of electricity consumption and spending of upper-middle income Cape Town households

	Number of households	Electricity Use (kWh/month)	Price (c/kWh) – 'Domestic-low' tariff	Monthly Electricity Spending
Medium Income	284 959	528	106.37	R 561.63
High Income	182115	930	106.37	R 989.24
Very High Income	35068	1033	106.37	R 1098.80

Weighting each of these income groups according to the proportion of middle-upper income households it represents, a mean value of R754.23 spent on electricity per month for each upper-middle income Cape Town household is obtained. This value is very close to the mean value of R744.99 reported by the sampled respondents. This is considered a reasonable approximation for the electricity consumption of upper-middle income Western Cape households more broadly.

The electricity spending data gathered in this survey is doubly-useful. In addition to its role as an explanatory covariate, this data also allows for the WTP values estimated by predictive models to be expressed as a percentage of existing electricity spending.

6.2.2: Psychographic Variables

Attitudes and values selected for inclusion as potential explanatory variables in this study were environmental norms, beliefs regarding climate change, perceptions of renewable energy, and attitudes towards nuclear power. The approach taken in measuring these variables and a summary of the results obtained are presented in this section, and summarised in Table 6.5.

Table 6.5: Psychographic variables: summary of results from attitudinal and value-based items

	n	Yes/ agree	No/ disagree	Don't know/ neither
People have a moral responsibility to take care of the environment".	436	0.94	0.03	0.03
"Do you consider yourself to be well informed on climate change?"	437	0.66	0.19	0.15
"Are you concerned about climate change?"	439	0.82	0.071	0.11
"Is climate change caused by human activity?"	432	0.64	0.087	0.27
"Are you familiar with renewable energy sources like wind and solar power?"	439	0.77	0.12	0.11
"Wind and Solar power will be major sources of electricity in the future."	435	0.72	0.04	0.23
"It is a good idea to get more of our electricity from renewable energy sources."	437	0.87	0.013	0.11
"Nuclear power is a clean and safe source of electricity"	434	0.15	0.42	0.43
"Would you prefer a programme that produced the same environmental benefits by replacing coal with nuclear power?"	432	0.19	0.40	0.42

Environmental Norms

The environmental norms held by respondents are assessed by item A5. This item asks respondents to indicate their agreement, neutrality, or disagreement with the statement "*People have a moral responsibility to take care of the environment".*

The results from this item did not vary substantially. Over 99% of respondents completed this item, and slightly over 94% of them agreed with the statement, whilst the 'disagree' and 'don't know' items each accounted for less than 3% of the responses. The proportion of respondents indicating their agreement was higher than expected – problematically so. Whilst encouraging from an environmental protection perspective, the data gathered by this item is of little value for use as a covariate in predictive models of WTP.

Attitudes towards Climate Change

The questionnaire contained items that sought to measure respondent perceptions relating to three aspects of climate change. Namely: 1) the extent to which respondents consider themselves well informed about climate change; 2) the extent to which respondents are concerned about climate change, and; 3) the belief that human activities are a major cause of climate change. These perceptions were assessed by Items A1, A3, and A7 respectively. The results of which are displayed in Table 6.5. All three of these items obtained response rates in excess of 98%. This finding supports the notion that climate change is regarded as a popular and relevant topic amongst the targeted population.

The responses to these items indicate that whilst only 66% of respondents considered themselves informed about climate change, and only 64% believed it to be man-made, a full 82% of respondents indicated that they are concerned about the effects climate change. Nearly four of every ten (37%) of respondents indicated that they do not believe human activities to be caused by humans by selecting the 'don't know' or 'disagree' responses.

Perceptions Related to Renewable Energy Technologies

Items included in the survey sought to examine three key perceptions or beliefs regarding renewable energy technologies. These were familiarity with renewable energy, support for renewable energy, and confidence in the potential of renewable energy technologies as a source of energy in the future. These beliefs were assessed by Items A2, A6, and A9 respectively.

As the results in Table 6.5 show, slightly over three quarters of sample indicated that they consider themselves familiar with renewable energy sources, and roughly the same proportion expressed confidence in renewable energy technologies as future energy sources. Slightly less than 90% of sampled respondents indicated their support for expansion in the use of renewable technologies for electricity generation.

Response rates of over 99% were observed for all three items related to renewable energy, lending further support to the notion that renewable energy, like climate change, is a current and popular topic of discussion amongst the target population.

Perceptions of Nuclear Energy

Two perceptions related to nuclear power were assessed by the survey. First of these, measured by item A8, is the perception that nuclear power is a clean and safe source of electricity. The second, measured by item B9, is the expression of a preference for nuclear power over renewable energy technologies as a substitute for coal and other fossil-fuels. Less than 15% of respondents indicated that they believe nuclear power to be clean and safe, whilst over 40% explicitly indicated that they do not regard it to be so.

Slightly less than 19% of the sample indicated that they would prefer that the Western Cape Provincial Government's green electricity target be replaced with a nuclear program producing equivalent environmental benefits. Amongst respondents who believe nuclear power to be clean and safe this figure rises to 42%, compared to only 14% amongst those who regard nuclear power to be dirty and dangerous.

The results for both of these items revealed a widespread aversion to nuclear power amongst the sampled respondents. This result is expected, as anti-nuclear sentiments have enjoyed something of a renaissance in the wake of the 2011 partial-meltdown at Japan's Fukushima Daiichi plant. Further, a recent survey conducted by the Department of Energy found that less than 5% of the aggregate population supported the use of nuclear power (Department of Energy, 2012). This aversion to nuclear power was evident in the resistance with which local environmental groups respondent to Eskom's recently announced plans for a large fleet of new nuclear power stations.

6.2.3: Behavioural Variables

Behavioural variables included in this study were ownership of a solar panel or solar water heating system, participation in earth hour, and participation in the recycling of some common household wastes.

Ownership of a solar water-heating system and participation in Earth Hour were assessed by items B7 and A4 respectively. The response data gathered from these items are presented in Table 6.6.

Table 6.6: Behavioural variables: Solar Geyser ownership and participation in Earth Hour

	n	Yes	No	Don't know
Does your household have a solar geyser or solar water-heating system?	439	0.14	0.86	-
Did your household take part in Earth Hour this year?	435	0.50	0.40	0.10

Solar Geyser Ownership

Slightly over 14% of survey respondents indicated that their household possessed a solar water heating system. Though no reliable population-level data on solar geyser ownership could be found, this figure is almost certainly higher than that of the wider population of Western Cape households. At 14%, the rate of solar-geyser ownership observed in this sample already exceeds the Western Cape Provincial Government's target of having solar water heaters installed on 10% of residential buildings by 2015 (Western Cape Provincial Government, 2010). This observation is consistent with the predictions of economic theory, which would expect higher rates of solar geyser ownership amongst middle-upper income households as a result of their greater propensity to purchase all assets, and the more favourable terms on which they can finance the high up-front costs of such systems.

The hypothesis that higher-income households are more likely to own a solar geyser is further supported by the strong positive relationship observed between income and solar geyser ownership within the sample. A chi^2 test found income to be positively related to solar geyser ownership, and this relationship is significant at 0.1%.

Earth Hour Participation

Just over half of the sample indicated that their households participated in earth hour, whilst 39.7% indicated that their households did not participate. The remaining 10% of respondents indicated that they did not know if their household participated.

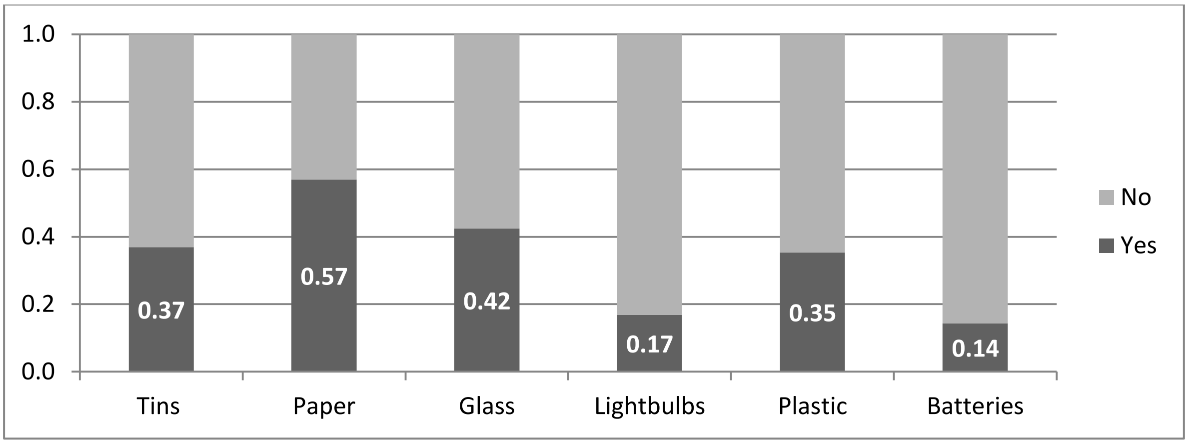
Though no data for aggregate earth hour participation rates is published, it seems very likely the rate of participation reported here is substantially higher than the aggregate rate of participation amongst the wider population of Western Cape households.

Recycling of Household Wastes

Survey item B3 sought to establish the status of respondent households as (non) recyclers of various household wastes. This item presented respondents with a list of waste categories, and asked them to indicate which of these, if any, their household recycled. Waste categories selected for inclusion were paper, tins, glass, plastic, batteries and light bulbs. The results from this item are presented in Figure 6.3 and Table 6.7 below.

Table 6.7: Number of wastes recycled by respondent household

No of Wastes Recycled	0	1	2	3	4	5	6
Proportion of Sample	0.29	0.17	0.16	0.134	0.15	0.05	0.04
Cumulative frequency	0.29	0.46	0.62	0.754	0.91	0.96	1.0



<u>Figure 6.3:</u> Wastes recycled by respondent household

Overall, 71% of the respondents surveyed indicated that their household engaged in recycling of at least one waste type. The mean number of waste types recycled by all sampled households was 2.0, with a standard deviation of 1.79. Amongst households who indicated themselves to be recyclers, the mean number of wastes recycled was 2.82, with a standard deviation of 1.48.

By far the most recycled waste was paper, which was reportedly recycled by more than half of respondent households. This was followed by glass, tins, and plastics, which were recycled by slightly over a third of households. As expected, batteries and light bulbs were the waste types least likely to be recycled. In part, this is attributed to the low prevalence of relevant infrastructure such as conveniently located collection points. These wastes are also typically generated in small volumes and on an infrequent basis, making their inclusion in waste disposal routines less likely. As a result, the recycling of these wastes requires greater individual initiative than is the case with more conventional wastes that are produced more regularly. Four respondents placed question marks over the 'light bulbs' item, which indicates that some people remain genuinely unaware that these items can and should be recycled.

6.3: Data Transformations

Prior to model estimation, the data was operationalized to produce covariates using the transformations detailed in Table 6.8 below:

Table 6.8: Summary of data transformations and variable creation

Characteristic	Expected Sign	Survey Item	Transformation (if any)
After-tax Household Income	Positive	B5	Values of between 1 and 10, corresponding to categories presented in the survey.
Respondent education in years	Positive	B6	Education takes a value equal to the minimum number of years required to obtain the selected qualification. See Table 6.6
Respondent Age	Negative	B1	
Respondent is female	Positive	B1	Takes a value of 1 if respondent is female; 0 otherwise.
Respondent is aware of and concerned about man- made climate change	Positive	A1, A3, A7	Takes a value of 1 if the respondent answered 'yes' to items A1, A3, and A7; 0 otherwise
Respondent has favourable views of renewable energy	Positive	A6	Takes a value of 1 if respondent agreed to item A6; 0 otherwise
Respondent confidence in renewable energy	Positive	A9	Takes a value of 1 if respondent agreed to item A9; 0 otherwise
Respondent supports Provincial Government's Green Electricity target	Positive	B8	Takes a value of 1 if respondent agreed to item B8; 0 otherwise
Respondent believes nuclear energy is clean and safe	Negative	A8	Takes a value of 1 if respondent agreed to item A8; 0 otherwise
Earth Hour Participation	Positive	A4	Takes a value of 1 if respondent answered 'yes' to item A4; 0 otherwise
Solar geyser ownership	Positive	B7	Takes a value of 1 if respondent agreed to item B7; 0 otherwise

The adjustments undertaken for the attitudinal and behavioural variables transformed them from categorical variables into binary variables based on a strict declarative interpretation of responses. This approach is appropriate for these variables; when assessing explanatory characteristics such as 'confidence in renewable energy' or 'concern regarding climate change' the variable of interest is the respondent's explicit endorsement of the statement or opinion. Further, it is widely observed that pro-environmental actions are seldom undertaken where substantial uncertainty or doubt remains about their benefits (Bird *et al.,* 2002), thus, for the purposes of this estimation, an 'unsure' answer corresponds more closely with a 'no' answer than a 'yes' answer. Further, interpretation of the variable relationships is simplified by the use of binary rather than categorical variables; responses are interpreted as a 'yes' or 'not yes', taking a value of one for a "yes/agree", and a value of zero otherwise.

This interpretation of responses may also mitigate the effects of the 'social desirability' biases which may be present in the responses to some items. People seldom publicly express overtly anti-environmental sentiments, and some individuals may feel awkward or guilty about their true feelings. This may compel them to misrepresent their opinions by selecting a neutral 'don't know/neither' response in place of their genuine 'no/disagree'.

The explanatory variables that this study uses used as covariates in multivariate econometric models are summarised in Table 6.9.

<u>Table 6.9:</u> Summary of the explanatory variables used in multivariate WTP models

Characteristic	n	Mean/ Proportion	Standard Deviation	Min	Max
Income	407	3.25	2.17	1	10
Education	434	14.45	2.52	10	20
Age	429	39.59	13.19	17	79
Gender	439	0.444	0.497	0	1
Climate Change attitudes	439	0.426	0.495	0	1
Favourable views of green energy	437	0.875	0.33	0	1
Confidence in renewable energy	439	0.722	0.44	0	1
Support for WC green electricity target	430	0.733	0.44	0	1
Believes Nuclear power is clean and safe	434	0.148	0.36	0	1
Earth Hour Participation	435	0.499	0.50	0	1
Solar Geyser Ownership	439	0.144	0.35	0	1

6.4: Results from the hypothetical market

This section presents the response data gathered by the items within the hypothetical market scenario presented in the questionnaire. As discussed in Section 4.2.3, the hypothetical market developed for this study made use of a double-bounded dichotomous choice elicitation format. The responses gathered by an elicitation item of this type can be used to create two distinct datasets. Considering the initial bid item in isolation, a response dataset identical to that which would have been obtained by a single-bounded dichotomous choice valuation item is obtained. When both the initial and follow-up bid items are considered, a double-bounded dataset is obtained, as discussed in Section 5.2.1. These response datasets are presented in Section 6.4.1 and 6.4.2, respectively. This chapter concludes with Section 6.4.3, which presents the results obtained from the follow-up item assessing respondent confidence in their answers to the dichotomous-choice WTP items.

6.4.1: Single-Bounded Dichotomous Choice Response Data

The single-bounded dichotomous choice response data obtained by considering the initial bid in isolation are summarised in Table 6.10. Alongside the raw (uncalibrated) response data, Table 6.10 presents the single-bounded data obtained when responses are calibrated according to the confidence that respondents attach to them. Calibrated response data are reported for threshold values of 50%, 70% and 100%. The threshold calibration approach is discussed in detail in Section 5.2.3.

Table 6.10: Summary of the single-bounded response data (cell values give proportion of 'yes' responses)

Bid Value	n	Uncalibrated responses	Calibrated: 50% threshold	Calibrated: 70% threshold	Calibrated: 100% threshold
R100	266	0.72	0.61	0.39	0.11
R150	173	0.64	0.53	0.33	0.09
	439	0.69	0.58	0.37	0.10

As expected, the probability of a positive response is lower for the respondents who were assigned the higher initial bid across all calibration threshold values.

6.4.2: Double-Bounded Dichotomous Choice Response Data

The value of the bid presented to each respondent in the follow-up item depends on their response to the initial dichotomous-choice item. Respondents who agreed to sign up for the *Green Power!* package were presented with a premium green-electricity package, at double the cost, whilst respondents who rejected the offer were presented with a starter green-electricity package at half the initial bid. The survey used two initial bid values, R100 and R 150. These initial bids correspond to the R50 – R100 – R200 and R75 – R150 – R300 bid vectors.

The responses gathered by these the initial and follow-up valuation items give rise to four possible response profiles, as discussed in Section 5.3.2. Once the results from the follow-up item are included, a double-bounded dataset is produced. This dataset is summarised in Table 6.11 below.

Table 6.11: Summary of double-bounded dichotomous choice responses

Bid Vector	n	Yes/Yes	Yes/No	No/Yes	No/No
R50- R100- R200	266	0.53	0.19	0.08	0.20
R75 - R150 – R300	173	0.41	0.23	0.15	0.21
		0.485	0.205	0.107	0.203

Table 6.12: Summary of WTP value-ranges for each response profile, by bid vector

Bid Vector	Yes/Yes	Yes/No	No/Yes	No/No
R50- R100- R200	[R200 ; ∞)	[R100 ; R200)	[R50 ; R100)	[R0 ; R50)
R75 - R150 – R300	[R300 ; ∞)	[R150 ; R300)	[R75 ; R150)	[R0 ; R75)

Slightly less than half of the sampled respondents gave a Yes/Yes response, agreeing to sign their household up for both *Green Power!,* and the higher-price follow-up bid. Around a fifth of the sample agreed to sign up for *Green Power!* but declined the offer to sign up for the more expensive package. The No/Yes response profile was the least populated for both bid vectors, accounting for only 11% of the aggregated sample. Only one in five respondents declined to sign up for either of the packages presented, thus falling into the No/No response profile.

Taken together, the responses to the double-bounded WTP items and the vector of bid values presented define bounds on respondent WTP. Table 6.12 shows the range of WTP values associated with each of the double-bounded response profiles.

The responses obtained from the two bid vector groups differ slightly, in line with expectations. Compared to respondents in the R50-R100-R200 bid vector, respondents assigned to the R75-R150-R300 bid vector were more likely to decline the initial bid, and those who accepted it were more likely to decline the higher-follow-up bid. Further, having declined the initial bid, respondents from the higher bid vector were almost twice as likely to accept the lower-priced package presented in the follow-up than those from the lower bid vector.

6.4.3: Reported Confidence in 'Yes' Responses

Immediately after answering the valuation items presented by the hypothetical market, respondents who replied in the affirmative were presented with a scale from 0-100% in 10% increments, and were asked to indicate how confident they were in their answers. As mentioned in Section 5.3.2, the inclusion of such a confidence measure is not standard practice in dichotomous-choice contingent valuation. However, it is intuitively obvious that the strength of the commitment represented by an agreement to purchase in the hypothetical market could vary widely between respondents. Where no provisions are made to assess the relative strengths of these commitments, this implies an assumption that all 'yes' responses are equivalent. Thus, in the standard conduct of contingent valuation studies, the validity of WTP estimates produced is directly dependent on the extent to which this implied assumption holds.

Table 6.13 presents the certainty estimates that respondents attached to their affirmative responses. Respondents who answered 'Yes' to both valuation items are assigned the higher of the two certainty estimates that they attached to their responses. These items achieved a high response rate – of the 350 respondents who answered 'Yes' to one or both of the dichotomous-choice valuation items, slightly over 98.5% proceeded to complete the follow-up confidence item.

Table 6.13: **Confidence expressed in 'Yes' responses to valuation items (n=345).**

Reported Confidence	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
Frequency	.014	.014	.026	.077	0.203	.14	.14	.149	.089	.15
Cumulative Frequency	.014	.028	.054	.131	.334	.474	.613	.763	0.85	1.00

Of the respondents who agreed to sign up for one or more of the G*reen Power!* products, 24% reported confidence of less than 50% in the sincerity of this commitment. Despite their affirmative response to the WTP item, these households are unlikely to be early-adopters - by their own assessment they are more likely to not sign up. Respondents who reported confidence of 50%-69% account for 34% of 'Yes' responses. These households are considered to be possible adopters of green electricity products, though further education and marketing initiatives may be required to convince them to sign up. Respondents who indicate confidence levels of 70% and over are considered likely adopters. These households account for 53% of the 'Yes' responses to the valuation items presented in the hypothetical market. Only 15% of the respondents who agreed to sign up for a *Green Power!* product reported that they were 100% sure that their commitment would be matched by their behaviour in the real world.

The reported confidence data could thus be used to classify households according to the likelihood of their purchasing a premium-priced green electricity product. This classification is shown in Table 6.14.

Table 6.14: **Households classified according to reported likelihood of purchasing green electricity**

	Will Not Adopt (No/No)*	Unlikely to Adopt	Possible Adopters	Likely Adopters
Reported Confidence	0%	10% - 49%	50% - 69%	70% - 100%
Proportion of Sample	0.21	0.11	0.27	0.42

**Households included in the 'will not adopt' category answered 'no' to both valuation items presented to them in the hypothetical market.*

6.4.4: Discussion of Hypothetical Market Results

Overall, slightly less than 80% of respondents indicated some positive willingness to purchase one or more of the *Green Power!©* products. Taking into account that the upper-middle income households considered in this study constitute around 47% of Western Cape Households, this gives an overall adoption rate of 37.2% of households. This is quite substantially higher than the rates of adoption observed in real-world voluntary-adoption green electricity markets, which seldom exceed 10% (Bird *et al.*, 2002; Elliott, 1999; Gallant & Fox, 2011; Wusthagen & Bilharz, 2006). Further, this predicted participation rate is very similar in value to the 42% found by Oliver *et al.* (2011).

If the dichotomous-choice responses presented in Table 6.10 – 6.12 were assumed to be accurate, unbiased, and honest reflections of respondent WTP, then the high incidence of Yes/Yes responses would suggest that the survey design was flawed, due to sub-optimally low bid values. If both of the bid values presented are lower than the maximum WTP of a large portion of the sample, then responses will be invariant across the presented bids, and the item will be insensitive to variations in respondent WTP. However, this explanation is considered unlikely. The *Green Power!* Products have an implied price premium of R0.25 per kWh, equivalent to around US$0.03 at the time of writing. This value represents a premium of around 25% on the basic price of electricity paid by most households. This is relatively high compared to the WTP estimates produced by other studies, and is comparable to the price premiums commanded by green electricity products sold in other countries (Bird *et al.*, 2002). The contention that the selected prices are sub-optimally low is also doubtful, considering that the City of Cape Town currently sells green electricity certificates at exactly this price. It is thus considered unlikely that the high incidence of 'Yes' responses obtained in this survey arose from poorly chosen bid values.

The high frequency of Yes/Yes responses and unrealistically high rates of predicted participation are thus most likely a result of some elements of bias in the responses, as discussed in Section 5.2. The notion that these responses are biased is further supported by the prevalence of cases in which Yes/Yes respondents reported the same level of confidence in the affirmative responses to both bids. It seems reasonable to expect that respondents who are less than 100% confident of their willingness to sign up for a product would be at least somewhat less confident of their willingness to purchase the follow-up good, which in effect offers the respondent an opportunity to purchase the initial package twice. Of the respondents who answered 'Yes' to both items, nearly 95% indicated a certainty level of below 100%, and 61% indicated the same confidence in their acceptance of both bids. This bias could arise from a number of possible sources, the most likely of which are now discussed.

A valuable hint as to the source of the bias can be gleaned from the 31% of respondents who reported the same confidence in their affirmative responses to the initial and follow-up items. Reporting the same confidence in the acceptance of both bids suggests one of two things; either respondents who intend to adopt a green electricity product do not regard the price as a major consideration in this choice; or, more likely, that respondents are not treating the bid items with the same gravity as real market transactions, and may be answering a different question from the one being asked. Rather than indicating their intention to purchase the good, respondents may be indicating their approval of green electricity, their support for the policy initiatives described, or their perception that the indicated price for the product is appropriate/fair (Schlapfer, 2008).

The reported confidence data summarised in Table 6.13 lend strong support to this interpretation. As these responses show, the 'yes' responses obtained from respondents vary widely in their (self-reported) strength as realistic commitments to purchase. The low confidence that many respondents expressed in their affirmative responses should give pause to those conducting or interpreting dichotomous-choice contingent valuation research without a confidence-measuring item. Further, the very low confidence reported by some respondents indicates that they themselves do not perceive a direct equivalence between the answers provided in the hypothetical market and their likely real world behaviour. The uncertainty that respondents express regarding the value of their hypothetical market responses as a guide to their behaviour as consumers could go some way towards explaining the large and persistent gap between WTP values estimated by contingent valuation studies and those revealed by real-world markets.

The inclusion of the confidence item allows respondents a chance to reveal their uncertainty regarding their agreement, and the reported confidence values provide a useful means for distinguishing genuine pledges to purchase from more general expressions of approval. This is done by applying a pre-estimation calibration threshold rule on the responses to the follow-up bid items, as discussed in Section 5.6.3.

One final possibility is that the bias may only affect the responses to the follow-up bid, and may be an unintended consequence of the double-bounded structure employed. If the hypothetical market is credible, then respondents should not anticipate the price change presented by the second bid item. If they regard the follow-up bid as a challenge to the truthfulness of their answer, then their response to the follow-up bid may be informed by their desire to meet or exceed the challenge, rather than a reasoned assessment of their actual willingness to pay the revised bid value (Harrison & Kriström, 1995). If this bias is present, it is easily detected, as it would result in the WTP estimates produced by double-bounded models substantially exceeding those produced by equivalent single-bounded models.

The results obtained from the hypothetical market and from the attitude-assessment items in the survey both indicate the existence of widespread support for the introduction of green electricity products amongst the upper-middle income population of the Western Cape. That such large portions of the sampled respondents take favourable views of green electricity products is evidence for the existence of potentially meaningful demand for these products from household consumers.

Though most respondents indicate themselves to be interested in, and supportive of, green electricity, most remain uncertain of their willingness to actually part with money for it. If these uncertain consumers could be convinced, they could form the basis for a rapid expansion of the residential green electricity market. Carefully targeted promotional and educational efforts emphasising the benefits of using green electricity and the real threat posed by man-made climate change could go some way towards convincing these consumers, and may produce strong participation growth in the market for green electricity products

Chapter Seven: Results
Estimating the Demand for Green Electricity

This section presents the results obtained from the application of the econometric models discussed in Section 5.3 to the hypothetical market data presented in Section 6.4 using the explanatory covariate data described in Section 6.2.

This chapter is structured as follows; the results from the non-parametric and parametric estimation models are presented in Sections 7.1 and 7.2 respectively. This is followed by an analysis of the aggregate WTP values implied by the results from these models in Section 7.3. This chapter concludes with a discussion of the WTP-covariate relationships observed in the multivariate estimation results.

7.1: Non-Parametric Models

The non-parametric model estimated in this study is adapted from the 'minimum legal WTP model developed by Harrison & Kriström (1995). As discussed in Section 5.2.2 and 5.3.1, this model makes use of the 'minimum legal WTP' interpretation of responses to dichotomous choice valuation items to produce a highly-conservative lower-bound estimate of the WTP values underlying the response data. This approach assigns each respondent a WTP value exactly equal to the highest bid which they have agreed to pay. The cumulative WTP distribution obtained when applying this interpretation to the raw (uncalibrated) hypothetical-market response data (presented in Section 6.4.2) is shown in Figure 7.1 below.

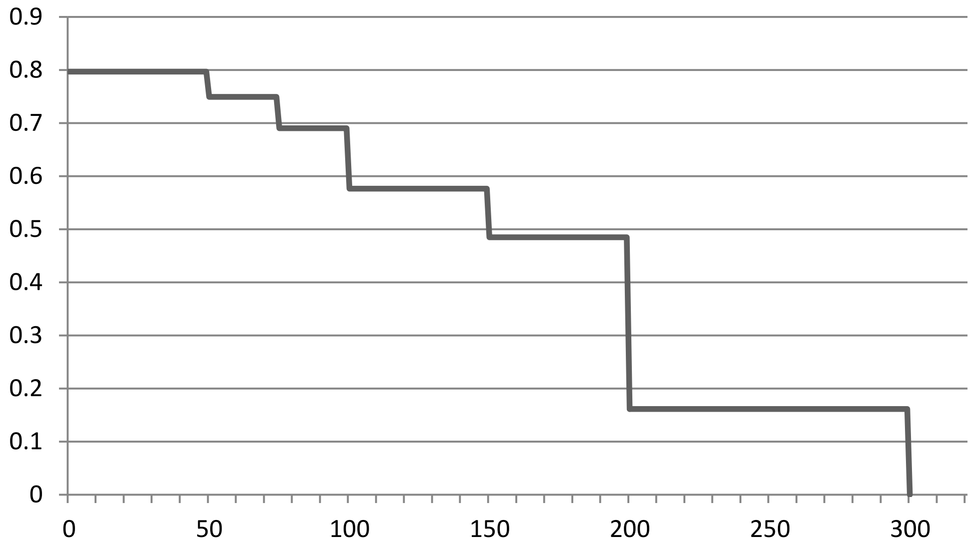


Figure 7.1: Cumulative Density Function of Non-parametric WTP (uncalibrated responses)

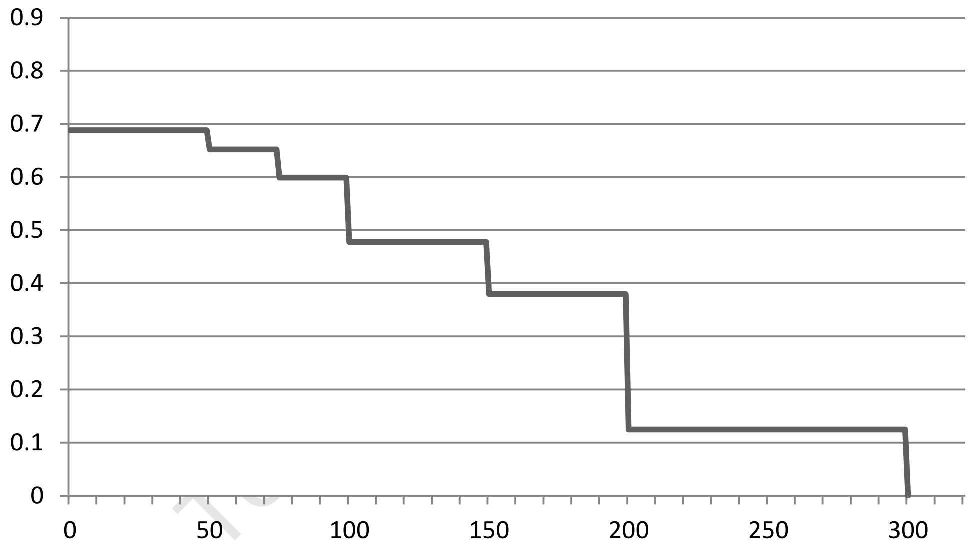


Figure 7.2: CDF of Non-parametric WTP (calibrated responses: 50% threshold)

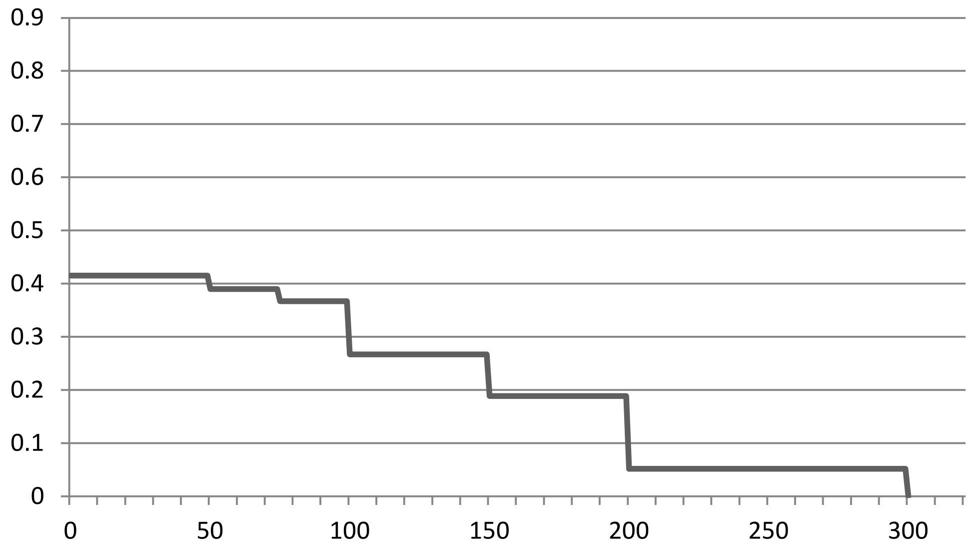


Figure 7.3: CDF of Non-parametric WTP (calibrated responses: 70% threshold)

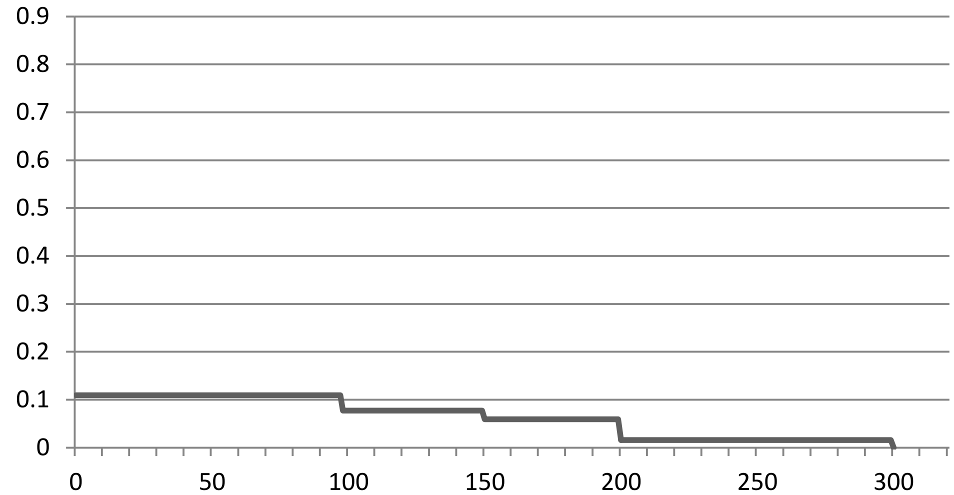


Figure 7.4: CDF of Non-parametric WTP (calibrated responses: 100% threshold)

Using the raw response data, the non-parametric model gives a mean WTP value of R145.10 per month, with a standard deviation of R100.52. This measure can be taken as a lower-bound estimate of the true mean WTP, subject to the assumption that the responses from the hypothetical market represent credible commitments to pay.

However, as discussed in Section 6.4.3 and shown in Table 6.13, many of the respondents who agreed to sign up for a *Green Power!* package reported low levels of confidence in the realism of their commitments. To examine the WTP changes produced when this reported uncertainty is considered, two further variants on the non-parametric model are estimated. These models attempt to account for respondent uncertainty by calibrating the response data according to the level of confidence in the response expressed by the respondent. The calibration process uses the confidence estimates that respondents attach to their answers to recode the response data from the valuation items. Where respondents indicate a level of confidence in their 'yes' response that falls below the chosen threshold value, their response is recoded as a 'no'. These models thus apply a stricter standard by assigning each respondent a WTP value equal to the highest bid value that they accepted with reported confidence greater than or equal to the chosen threshold value.

Following Champ *et al.* (2002), threshold confidence values of 50% and 70% were selected. These certainty thresholds correspond roughly with 'probably yes' and 'yes' responses that could be used in surveys with valuation items that elicit categorical rather than binary responses.

When applied to hypothetical market responses calibrated at a threshold value of 50%, the non-parametric model produced the cumulative WTP distribution shown in Figure 7.2. This model gives a mean WTP value of R121.13 per month, with a standard deviation of R103.10. Using response data calibrated at a threshold value of 70%, the non-parametric model produces the cumulative WTP distribution is shown in Figure 7.3. The corresponding mean WTP value is R67.65 per month, with a standard deviation of R92.52.

To obtain the absolute lower-bound estimate of WTP implied by these data, a non-parametric model was estimated using responses calibrated with a threshold value of 100% confidence. This model imposes the strictest possible requirements on the response data; respondents who indicate any doubt at all about the credibility or realism of their agreement to purchase are assigned a WTP value of zero. Imposing this threshold reduces the proportion of respondents indicating a positive WTP from 79.7% to just 10.9%. The cumulative WTP distribution produced by the non-parametric models using data calibrated at a 100% threshold is shown in Figure 7.4. This model produced a mean WTP value of R 19.36 per month, with a standard deviation of R 59.40.

Summary of Non-Parametric Models

The estimates of mean WTP produced by the non-parametric models are intended to serve as a baseline, or lower-bound estimate of the WTP values that could be derived from the hypothetical market data. If appropriately aggregated, they provide a conservative estimate of the total contribution that consumers would be willing to make towards the attainment of the Western Cape Provincial Government's 15% green electricity target.

The mean WTP values and predicted rates of participation estimated by the non-parametric model vary widely with the level of reported confidence at which the response data was calibrated. The mean WTP estimated using a threshold value of 100% is only 13.3% of the value obtained from the uncalibrated model. Further, response-calibration was found to reject the hypothetical purchases of up to 86.3% of respondents who agreed to sign up for one or more of the *Green Power!* products.

The relationship between the non-parametric estimates of mean WTP and the level of reported confidence chosen as the calibration threshold is depicted in Figure 7.5 and summarised in Table 7.1.

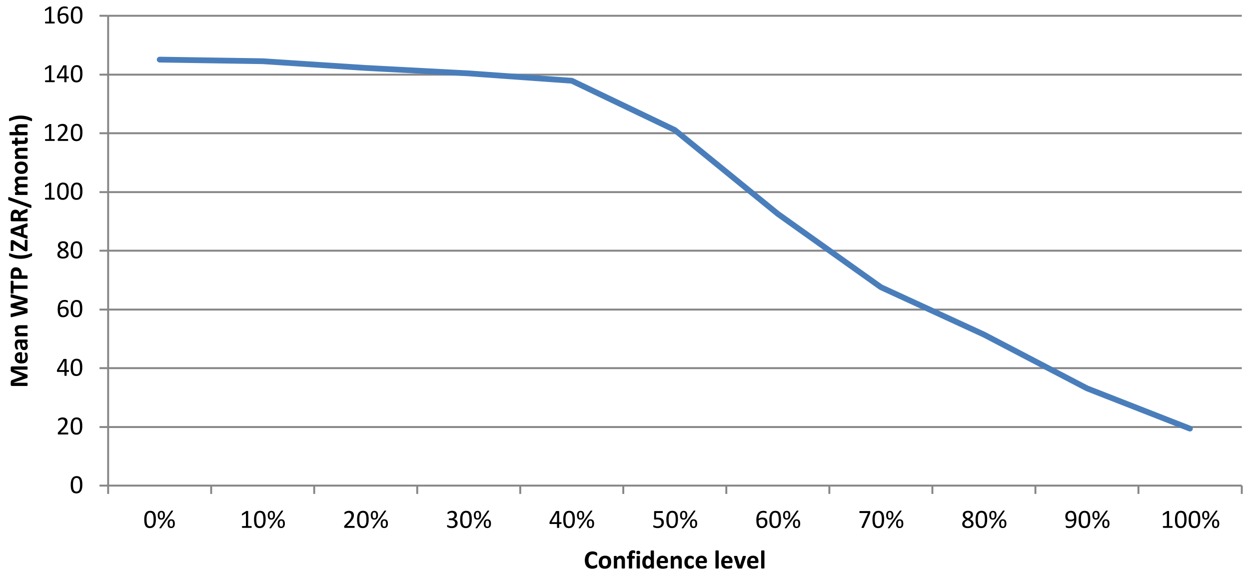


Figure 7.5: Non-parametric mean WTP estimates and threshold confidence level.

The use of a response calibration instrument could be criticised for introducing an element of subjectivity to the valuation exercise through the choice of threshold values. Since theory suggests no obviously correct threshold value, this crucial determinant of value estimates is effectively left to researcher discretion. Further, the claim that altering response data produces more realistic WTP estimates poses a direct challenge to the most fundamental assumption of the contingent valuation methodology; that responses in the hypothetical market are a reliable proxy for real behaviour.

Responding to these criticisms, it is important to note that this subjectivity is simply unavoidable. Where researchers do not measure reported confidence and simply use raw responses, they are simply selecting zero as the threshold value for calibration. Thus, in a very real sense, there are no truly uncalibrated contingent valuation studies – only studies that have adopted their threshold values unknowingly and without examination. Moreover, by considering all 'Yes' responses to be equally valid the standard approach interprets responses in the most lenient manner possible. This finding could go some way towards explaining why contingent valuations consistently exaggerate real world WTP and participation rates. Finally, response calibration does not violate the assumption that stated preferences can serve as a reliable guide to real-world behaviours, but rather seeks to develop a more nuanced understanding of their relationship.

Table 7.1: Mean WTP values for non-parametric models at different threshold certainty values.

Threshold Confidence Value	Estimated Mean WTP (ZAR/Month)	Standard Deviation
Uncalibrated	145.10	100.52
10%	144.53	100.86
20%	142.26	101.61
30%	140.43	102.57
40%	137.87	104.12
50%	121.13	103.10
60%	92.59	103.68
70%	67.65	92.52
80%	51.48	86.22
90%	33.14	79.95
100%	19.36	59.40

7.2: Parametric Models

This section presents the results from the application of the parametric models discussed in Section 5.3.2. The results from single-bounded models are presented first, followed by the results from double bounded models. The section concludes with an analysis of the WTP-covariate relationships observed in the multivariate models.

7.2.1: Single-Bounded Models

Table 7.2: Coefficients reported by Single-bounded logit and probit models

	Logit Model		Probit Model	
	Coefficient	**dy/dx**	**Coefficient**	**dy/dx**
Initial bid value	-0.0088 *(0.005)	-0.015* (0.008)	-0.0053 * (0.0029)	-0.0008*** (0.00027)
After-tax Household Income	0.130 ** (0.066)	0.0224** (0.011)	0.078** (0.039)	0.0266** (0.0132)
Respondent education in years	-0.104 * (0.0614)	-0.0178* (0.0104)	-0.059 * (0.036)	0.0233** (0.0127)
Respondent Age	-0.025 ** (0.0097)	-0.0042*** (0.0016)	-0.0146*** (0.0056)	-0.0022 (0.0018)
Respondent is female	0.455 * (0.253)	0.078* (0.043)	0.2598 * (0.147)	0.061 (0.048)
Respondent is aware of and concerned about man- made climate change	0.968 *** (0.273)	0.170*** (0.0467)	0.564 *** (0.156)	0.165 *** (0.049)
Respondent has favourable views of renewable energy	0.815 * (0.419)	0.157* (0.088)	0.514 ** (0.246)	0.162** (0.079)
Respondent confidence in renewable energy	0.209 (0.287)	0.0368 (0.0514)	0.116 (0.169)	0.139** (0.05)
Respondent considers the 15% green electricity target worthwhile	0.896 *** (0.297)	0.172 *** (0.06)	0.5296*** (0.177)	0.153** (0.06)
Respondent believes nuclear energy is clean and safe	-0.326 (0.325)	-0.0576 (-0.059)	-0.1854 (0.193)	-0.083 (0.073)
Earth Hour Participation	0.274 (0.249)	0.0476 (0.0435)	0.152 (0.146)	0.033 (0.048)
Solar geyser ownership	0.652 (0.398)	0.105* (0.058)	0.385 * (0.223)	0.165** (0.066)
Constant term	1.76 (1.09)		1.01 (0.637)	
Mean WTP	**R228.82**		**R227.13**	

Table 7.3: **Model Statistics for single-bounded logit and probit models**

	Logit Model	Probit Model
Mean WTP (full model)	R228.82	R227.13
Mean WTP (bid only)	R228.48	R230.47
95% Confidence Interval	(-R301.14; R777.94)	(-R202.50; R763.89)
Log Likelihood	-207.477	-207.472
Wald Chi ^{2}	64.47 (0.0000)	72.36 (0.0000)
Pseudo – R^2	0.1682	0.1683
AIC	440.95	440.94
Correctly classified	334/439 (76.08%)	334/439 (76.08%)

The results from the single-bounded logit and probit models presented in Tables 7.2 and 7.3 are very similar, confirming the popular wisdom that for analysis of dichotomous choice response data the choice between these specifications is essentially arbitrary (Carson & Hanemann, 2005). The Wald chi^2 test shows both models to be significant at all levels, and both correctly predict 76% of the initial bid responses. The models produce similar mean WTP values of R232.78 and R230.59 per month respectively. Median WTP estimates are marginally lower than mean for both models, though only by around R5 (which is less than 3%). In both cases, the full multivariate models produced mean WTP estimates that closely approximated those of their bid-only equivalents. With the exception of education, all of the covariate relationships correspond with those expected, and the marginal effects of each variable are remarkably similar in both models. The primary difference between the models is that the 95% confidence interval estimated by the logit model covers a wider range of values by a margin by around 10%.

In both models, the bid coefficient is negative, implying the downwards sloping demand curve expected of a normal or luxury good. A marginal increase in the Rand value of the initial bid reduces the probability of respondent acceptance by 2%.

Calibrated-Response Logit Models

The standard approach taken in contingent valuation studies using dichotomous-choice elicitation items is to count each 'yes' response as a 'purchase' in the hypothetical market. The response-calibration approach discussed in Sections 5.2.3 and 6.4.3 essentially seeks to refine this process by requiring that responses meet a more stringent set of criteria in order to be considered as 'purchases' in the hypothetical market.

To examine the effects of response calibration in parametric estimations, logit models were estimated run using the initial-bid response data calibrated at threshold values of 50% and 70%. These threshold certainty values were intended to correspond roughly with a respondent's assessment that their household is 'likely' or 'very likely' to actually sign up.

Table 7.4: Coefficients reported from Logit models using certainty-calibrated response data

	Logit Model *calibrated responses (50% threshold)*		**Logit Model** *calibrated responses (70% threshold)*	
	Coefficient	**dy/dx**	**Coefficient**	**dy/dx**
Initial bid value	-0.01** (0.005)	-0.002** (0.0009)	-0.00837 * (0.0046)	-0.0017* (0.0009)
After-tax Household Income	0.171*** (0.632)	0.033*** (0.012)	0.1525*** (0.059)	0.031*** (0.011)
Respondent education in years	-0.0305 (0.057)	-0.006 (0.01)	-0.005 (0.055)	-0.01 (0.011)
Respondent Age	-0.021** (0.009)	-0.004** (0.0017)	-0.0064 (0.0086)	-0.0013 (0.0017)
Respondent is female	-0.0014 (0.236)	0.0002 (0.046)	0.141 (0.229)	0.029 (0.046)
Respondent is aware of and concerned about man- made climate change	0.76*** (0.246)	0.149*** (0.046)	0.52** (0.228)	0.108** (0.047)
Respondent has favourable views of renewable energy	0.856** (0.428)	0.168** (0.083)	0.409 (0.502)	0.083 (0.066)
Respondent confidence in renewable energy	0.180 (0.28)	0.035 (0.055)	0.604** (0.285)	0.12** (0.054)
Respondent considers the 15% green electricity target worthwhile	0.793*** (0.292)	0.156 *** (0.055)	0.778** (0.315)	0.154 (0.058)
Respondent believes nuclear energy is clean and safe	-0.725** (0.325)	-0.14** (0.063)	0.0085 (0.315)	-0.0017 (0.064)
Earth Hour Participation	0.264 (0.239)	0.0518 (0.465)	0.430* (0.234)	0.088* (0.048)
Solar geyser ownership	0.451 (0.360)	0.089 (0.07)	0.402 (0.315)	0.083 (0.066)
Constant term	0.538 (1.03)		-1.85** (1.075)	
Mean WTP	**R160.48**		**R46.50**	
95% Confidence Interval	(R132.73; R315.17)		(-R347.84; R365.80)	

Table 7.5: Model statistics for Logit models using calibrated response data

	Logit model (50% calibration)	Logit model (70% calibration)
Mean WTP	R160.48	R46.50
95% C.I.	(R132.73; R315.17)	(-R347.84; R365.80)
Log Likelihood	-230.55	-234.21
Wald Chi ^{2}	61.90 (0.0000)	72.73 (0.0000)
Pseudo – R^2	0.1485	0.1683
AIC	487.10	494.42
Correctly classified	293/439 (66.74%)	232/439 (52.85%)

As these results show, imposing certainty-threshold calibration on the single-bounded response data sharply reduces the WTP estimates produced by the logit model. Mean WTP values of R160.47 and R46.44 were obtained for the 50% and 70% threshold values respectively. Compared to the model using uncalibrated responses, this corresponds to a reduction in mean WTP of 31% and 80% respectively. The substantial declines in mean WTP produced by calibrating the response data serve as further proof of the importance of the approach taken in interpreting uncertain responses as a determinant of the valuations produced.

Though both models remain significant at all levels, the calibrated-response logit models are notably less powerful predictors of their input data than the uncalibrated model. The logit models run using the responses calibrated at the 50% and 70% thresholds correctly predicted the (calibrated) responses of around two-thirds and one half of respondents. This compares relatively poorly with the 76% of responses correctly predicted by the uncalibrated model. The weaker predictive power of the calibrated response models is also evident in their larger log-likelihood and AIC values.

Whilst they do provide an interesting metric with which the results from other models can be compared, care should be taken when interpreting the results from the single-bounded models presented in this section. The hypothetical market presented in the survey used only two initial bid values, which is less than would typically be desired for single-bounded models (Carson & Hanemann, 2005).

7.2.2: Double-Bounded Models

The merits of double-bounded dichotomous choice elicitation items and the validity of the WTP estimates they produce are the subject of much debate. A classic examination of the double-bounded dichotomous choice format is offered by Hanemann *et al.* (1991), who find double-bounded models to produce substantial efficiency gains compared to their single-bounded equivalents. However, this finding is not universally accepted, and many subsequent examinations have found cause for caution when using double-bounded elicitation items. A good example of this is the work of Harrison & Kriström (1995), who find little to recommend the use of the double-bounded dichotomous choice format, and recommend strongly against it.

Two double-bounded parametric models were employed in this analysis; the bivariate probit model proposed by Cameron & Quiggin (1994) and the interval-data model proposed by Hanemann *et al*. (1991). The results of these estimations are presented in Tables 7.6 and 7.7

The results produced by these models are generally consistent with expectations; both models find a negative relationship between the bid values presented to respondents and the likelihood of acceptance, and this relationship is statistically significant at 5%. The covariates found to be significantly related to WTP include income, education, perceptions of renewable energy, beliefs regarding climate change, and solar geyser ownership. The relationships observed are also mostly in line with expectations, education again being the sole exception. A more comprehensive analysis of the covariate relationships observed in each model is presented in Section 7.6.

Table 7.6: **Estimated coefficients from double-bounded models**

	Bivariate Probit Model		**Interval-data Model**	
	Coefficient (R1)	**Coefficient (R2)**	**Coefficient**	**Marginal Effect**
Initial bid value	-0.0071** (0.0029)			-0.0008*** (0.00027)
Follow-up bid value		-0.0046*** (0.001)		-0.0011*** (0.0003)
After-tax Household Income	0.0762 ** (0.038)	0.064 * (0.0355)	12.79 ** (6.12)	0.0266** (0.0132)
Respondent education in years	-0.059 (0.037)	-0.058 * (0.033)	-11.28 ** (5.615)	0.0233** (0.0127)
Respondent Age	-0.0134 ** (0.0053)	-0.0029 (0.0053)	-1.16 (0.858)	-0.0022 (0.0018)
Respondent is female	0.192 (0.146)	0.141 (0.127)	29.29 (23.14)	0.061 (0.048)
Respondent is aware of and concerned about man- made climate change	0.532 *** (0.236)	0.384 *** (0.141)	80.57 *** (24.64)	0.165 *** (0.049)
Respondent has favourable views of renewable energy	0.506 ** (0.236)	0.361 * (0.209)	81.89 ** (38.66)	0.162** (0.079)
Respondent confidence in renewable energy	0.168 (0.164)	0.397 *** (0.149)	60.61 ** (26.51)	0.139** (0.05)
Respondent considers the 15% green electricity target worthwhile	0.545 *** (0.178)	0.316 * (0.172)	72.49 ** (29.06)	0.153** (0.06)
Respondent believes nuclear energy is clean and safe	-0.150 (0.215)	-0.226 (0.187)	-36.89 (32.50)	-0.083 (0.073)
Earth Hour Participation	0.139 (0.144)	0.065 (0.127)	15.68 (23.17)	0.033 (0.048)
Solar geyser ownership	0.393 * (0.219)	0.451 ** (0.195)	81.74 ** (34.08)	0.165** (0.066)
Constant term	1.14 * (0.604)	0.721 (0.542)	166.098 ** (84.707)	
Mean WTP	**R196.43**	**R235.33**	**R227.76**	
Standard Deviation			**(R101.33)**	

Table 7.7: Model statistics for double-bounded estimation models.

	Bivariate Probit Model	Interval Data Model
Mean WTP	Mean Value: R215.88	R227.76
Wald Chi^2	129.29	63.61
Log Likelihood	-442.48	-452.38
Initially Correctly Classified Count	301/400	-
Fully Correctly Classified Count	250/400	-
AIC	938.96	930.77
Rho	Full model: 0.9076 Bid Only: 0.8786	-

As explained in Section 5.3.2, the choice between the bivariate probit and interval-data models depends largely on the validity of the assumption that the responses to both bids are determined with reference to the same unchanging WTP value. A convenient measure of this joint-determination is provided by the rho value estimated for the bivariate probit model. Rho measures the correlation between the error terms from the two response equations, taking on a value between -1 and 1, where -1 indicates perfect negative correlation, zero indicates that the responses are separately determined, and 1 indicates perfect joint-determination.

The value of rho for this bivariate probit model is 0.9076 for the full model including covariates, and 0.8786 for the bid-only model. This indicates a strong correlation between the response-generation functions, and supports use of the Hanemann *et al*. (1991) interval-data model as the preferred double-bounded specification (Alberini, 1995; Abdullah & Jeanty, 2012; Balana *et al*., 2012).

Since the bivariate probit model estimates two WTP values – one for each bid equation – the mean WTP of the overall model is obtained by taking the mean of these values, producing a mean monthly WTP of R215.88.

The estimates of mean WTP produced by the double-bounded models are not too different from those of the single-bounded models, with all values falling in the range of

R210-R230 per month. These similarity in magnitude of the single and double-bounded estimates confirms that the double-bounded elicitation format is not itself a source of bias, as discussed in Section 6.4.4.

The preferred interval-data model estimates mean WTP to be R227.76, with a standard deviation of R101.60, whilst median WTP is R235.41. The mean WTP for the bid-only interval data model is R231.49. The coefficients reported for the interval data model indicate the marginal effect of each variable on the estimated WTP value, thus, marginal effects are not separately reported for this model.

7.3: Post-estimation Calibration

The WTP values produced by the preferred interval-data model are further transformed using post-estimation certainty calibration. Rather than adjusting the response data prior to estimation, this approach estimates models using the raw response data, and then adjusts the estimated WTP value for each respondent according to their reported confidence in their agreement to purchase.

Two approaches were taken in this regard. The first approach weights the WTP values predicted for each respondent according to the confidence they reported in their agreement to purchase. Thus, the individual WTP values predicted by the interval data model are proportionally reduced according to the respondent's reported uncertainty. This confidence-weighted WTP measure is unique amongst models in this study, in that it alone makes full use of the reported-confidence data.

Secondly, a post-estimation variant of the threshold calibration approach is proposed. The interval-data model is run using the raw responses, and the WTP estimates produced are then calibrated by assigning a WTP of zero to all individuals whose reported confidence in their hypothetical market responses falls below the selected threshold value.

Taking C_1 and C_2 to denote the levels of confidence that respondents report in their 'Yes' responses to the initial and follow-up bids respectively, the calibrated estimates produced by the certainty-weighted approach are given by:

$WTP_{cw} = C_{CW} = WTP_e \times C_1$ *for Yes/No and No/No respondents*

$WTP_{cw} = C_{CW} = WTP_e \times C_2$ *for Yes/Yes and No/Yes respondents*

Whilst the responses calibrated using the post-estimation confidence-threshold approach are given by:

$WTP_{CT} = WTP_e$ if $C_1 >= T$ or $C_2 >= T$

$WTP_{CT} = 0$ if $C_1 < T$ and $C_2 < T$

Where WTP_e, WTP_{cw} and WTP_{CT} respectively denote the estimated, confidence-weighted, and threshold-calibrated WTP estimates, whilst T represents the threshold confidence value according to which the responses are calibrated.

These post-estimation approaches to calibration are based on a conception of respondents as having 'thick indifference curves' for environmental goods. Whilst they may prefer environmentally friendlier products, this preference may not affect their consumption choices if the utility gain from switching is not greater than some threshold value (Hanemann & Kanninen, 1998). Even where their preferences are such that signing up for a green electricity product would yield them a net increase in utility, it is not certain that respondents will do so. Thus, the certainty values provided by respondents may indicate the probability that they would sign up, given that their WTP exceeds the price, rather than uncertainty regarding their willingness to purchase the good at the offered price.

Three such WTP distributions were produced using estimates from the double-bounded interval data model. These were a confidence-weighted model, and two post-estimation threshold-calibrations for 50% and 70% threshold values. Summary statistics for these models are presented in Table 7.8.

<u>7.4: Summary of WTP estimates</u>

Table 7.8 presents a summary of the WTP estimates produced by all of the valuation models used in this study. The mean monthly WTP value for each model is presented alongside the implied price-premium relative to the mean reported monthly electricity spending of R745.

<u>Table 7.8</u>: **Summary of WTP estimates produced by all models**

	Model	Description	Mean Monthly WTP	Price premium (%)
Models using Uncalibrated response data	**Non-parametric WTP**	Non-parametric model with uncalibrated response data	**R145.10**	19.5%
	Logit	Single-bounded logit model	**R228.82**	30.7%
	Probit	Single bounded probit model	**R227.13**	30.5%
	Bivariate Probit	Double-bounded bivariate probit model	**R215.88**	29.0%
	Interval Data	Double-bounded interval data model.	**R227.76**	30.6%
	Interval Data (Bid-only)	Interval Data model without covariates	**R231.48**	31.1%
Models using calibrated response data	**Non-parametric WTP50**	Responses subject to 50% certainty calibration	**R121.13**	16.3%
	Non-parametric WTP70	Responses subject to 70% certainty calibration	**R67.65**	9.1%
	Non-parametric WTP100	Responses subject to 100% certainty calibration	**R19.36**	2.6%
	Logit (50%)	Responses subject to 50% certainty calibration	**R160.47**	21.5%
	Logit (70%)	Responses subject to 70% certainty calibration	**R 46.44**	6.2%
Post-Estimation calibration models	**Interval Data CW**	Interval data estimates calibrated using confidence weighting	**R123.47**	16.6%
	Interval Data 50P	Interval data estimates: threshold calibrated (50%)	**R170.04**	22.8%
	Interval Data 70P	Interval data estimates: threshold calibrated (70%)	**R106.42**	14.3%

The WTP values estimated by the parametric models using uncalibrated responses do not vary widely between alternative specifications, ranging from R215.88 per month for the bivariate probit model, to a maximum of R231.48 per month for the bid-only interval-data model. These values correspond to a price premium of approximately 30%. The mean WTP values produced using the uncalibrated response data are bounded at the low end by the non-parametric minimum-legal-WTP model, which finds a mean value of around R145 per month, equivalent to a premium of 19.5%.

The results from calibrated models vary widely between approaches, and according to the threshold values selected. The results indicate that models using pre-estimation response calibration generally produced greater reductions in WTP estimates than models using the same threshold values for post-estimation WTP calibration.

Though it is standard practice for contingent valuation studies to settle on a single representative WTP value, this seems a rather bold move in this case. The study of demand for green electricity in South Africa is in its infancy, and the information available in this regard is extremely limited. Further, WTP estimates vary widely between models, and there is no obvious external standard to which these results can be compared as a check on their validity. Thus, it seems more appropriate that the results of the valuation conducted in this study be given as a range of values. The results from the double-bounded interval-data model of Hanemann *et al.*, (1991) define the upper bound on this range, with a mean WTP estimate of R227.76 per month. The lower bound on this range of values is defined by the non-parametric model using response data calibrated at 70% certainty, which gives a mean monthly WTP of R67.65.

This study thus finds upper-middle income Western Cape households to have a mean monthly WTP for green electricity products that falls within the range of R67.65 to R227.76. This corresponds to a price premium of 10% to 30% for a typical household.

The price premium implied by the results from the upper-bound Interval Data model is just over 30%, which is consistent with the 26% premium found by Oliver *et al.* (2011). However, these comparisons are complicated by changes in the basic price of electricity since 2007-8 and the exclusive focus on upper-middle income households in this study. A full comparison of the results found in this study with those of previous South African green electricity valuation studies can be found in Chapter 9.

7.5: WTP Aggregation

To obtain an estimate of the aggregate WTP of upper-middle income Western Cape households for the attainment 15% green electricity target, the representative WTP values summarised in Table 7.8 must be aggregated across the relevant population (Hanley & Spash, 1993; Arrow *et al.,* 1993; Carson & Hanemann, 2005). As discussed in Section 4.1, the population of interest to this study is defined to include the 460448 electrified upper-middle income Western Cape households (Western Cape Provincial Government, 2010).

Table 7.9 provides a summary of the aggregate WTP values obtained from the mean household WTP values computed from each of the models estimated in this study.

Table 7.9: Summary of aggregate monthly WTP estimates

	Mean WTP	Aggregate WTP for upper-middle Income Households (460448)
Non-Parametric WTP	R145.10	R 66 811 005
Logit	R228.82	R 105 359 711
Probit	R227.13	R 104 581 554
Bivariate Probit	R215.88	R 99 401 514
Interval Data	R227.76	R 104 871 636
Non-Parametric WTP50	121.13	R 55 774 066
Non-Parametric WTP70	R67.65	R 31 149 307
Non-Parametric WTP100	R19.36	R 8 914 273
Interval Data CW	R123.47	R 56 851 514
Interval Data 50%P	R170.04	R 78 294 577
Interval Data 70%P	R106.42	R 49 000 876

The results from this study thus indicate that upper-middle income Western Cape Households have an aggregate WTP of between R31.1 million and R104.9 million per month.

7.6: Examination of WTP-Covariate Relationships

This section examines the relationships that the econometric modelling process revealed between various covariate factors and estimated WTP. Demographic, attitudinal, and behavioural covariates are examined, followed by an examination of the WTP-differences amongst respondents according to the bid-vectors presented to them.

7.6.1: Demographic Factors

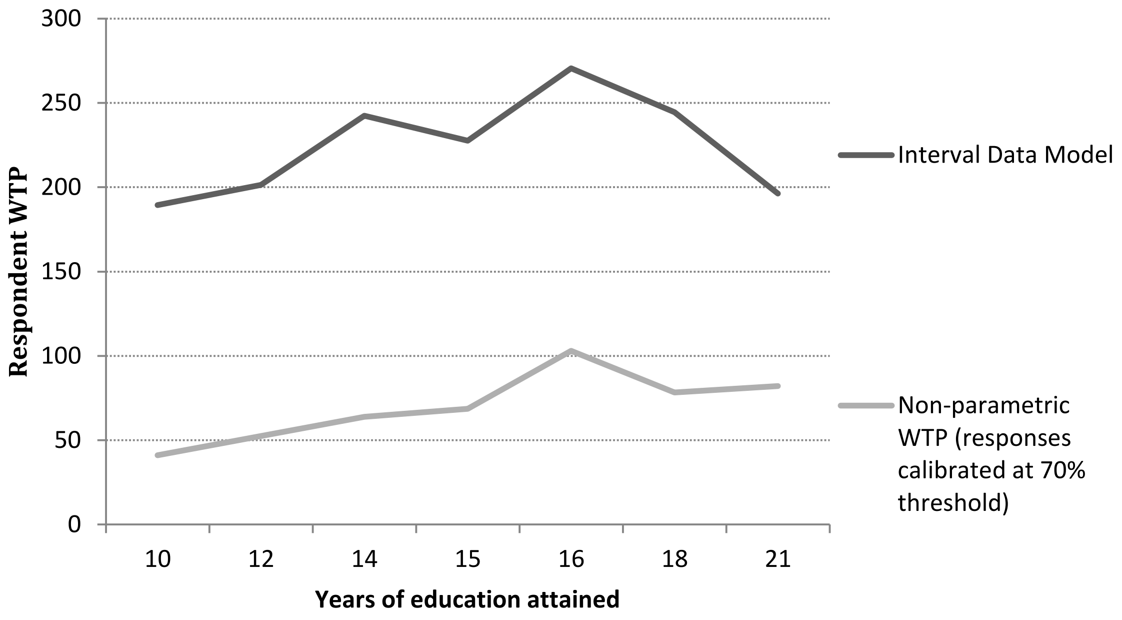
In all multivariate models, most of the chosen demographic covariates were found to be related to WTP in a manner consistent with our expectations and economic theory. Income was found to be positively related to WTP by all models, and this relationship was highly significant in all specifications. The preferred upper-bound interval-data specification found that on average, an increase of R10 000 in monthly incomes corresponds to a WTP increase of R12.79 per month.

As anticipated, all models found female respondents found to have higher WTP for green electricity products than did their male counterparts. The preferred interval-data model estimated a mean WTP of R258 per month for female respondents, compared to R203 for males. The anticipated negative relationship between age and WTP was also observed across model specifications, indicating that, in general, WTP is higher amongst younger respondents. However, both age and sex fared poorly as covariates; though the expected relationships were observed in all models, these relationships were not statistically significant. The only exceptions in this regard were the single-bounded logit and probit models, which found the negative relationship between age and WTP to be significant at 5%.

All multivariate WTP models used in this study found a negative relationship between respondent education and WTP for green electricity which was consistently significant at 10% or better. Whilst it is generally expected that pro-environmental sentiment (and thus WTP for environmental goods) would vary positively with education, there is no reason to expect this result to apply uniformly for all green products, or at all levels of education (Rex & Baumann, 2006). Indeed, a negative relationship between WTP and education could be anticipated in some cases, as more educated respondents are likely to engage more critically with the scenario presented to them in the hypothetical market. Particularly, where there are reasons to doubt the benefits associated with a particular technology, more educated respondents are more likely to be familiar with such reasons.

The negative relationship observed here may thus be partially attributable to a growing scepticism regarding the merits of renewable energy technologies, which have recently been the subject of a number of unfavourable reviews regarding their costs, environmental benefits, and impacts on wildlife and people (Gallant & Fox, 2011; Menzies, 2011). Moreover, it is important to note that the negative WTP-education relationship is not consistent across all levels of education. The WTP-education relationship is graphically depicted in Figure 7.6, which shows how the mean WTP estimates from the preferred upper and lower bound models change with education.

As Figure 7.6 shows, WTP for green electricity is increasing in education up to sixteen years, after which it declines. In terms of qualifications, this means that WTP is positively related to educational attainment up to an honours-degree level, but declines with the progression to higher postgraduate qualifications.



<u>Figure 7.6</u>: Estimated relationship between WTP and education

This relationship is intuitively plausible; relatively uneducated individuals may lack exposure to (or information regarding) environmental issues and renewable energy sources. As a respondent's education increases, so too does the likelihood of their having been exposed to these issues. In the aggregate, more educated respondents could be expected to have progressively more advanced knowledge of the relevant environmental issues and the benefits renewable energy technologies, so increasing their WTP. However, serious questions remain unanswered about the merits and cost effectiveness of renewable energy technologies as a remedy for environmental problems, and many people believe their environmental benefits have been exaggerated (Gallant & Fox, 2011). Respondents with postgraduate qualifications may be better informed regarding these issues, or may simply engage more sceptically with the benefits claimed in the hypothetical scenario.

The household electricity spending variable was consistently found to be an insignificant predictor of both participation and WTP, and was removed from multivariate analyses on the basis of likelihood-ratio tests.

The results of this study broadly confirm that demographic variables are generally weak predictors of responses in the hypothetical market.

<u>7.6.2: Psychographic variables</u>

The results of the estimations undertaken in this study confirm the widely-observed finding that attitudinal/psychographic characteristics are superior to demographic variables as predictors of respondent WTP for environmental goods (Wiser, 2006; Arkesteijn & Oerlemans, 2005).

A respondent's attitudes towards and perceptions of climate change were found to be a powerful predictor of their WTP; the 'climate change attitudes' variable was positively related to WTP in all models, and this relationship was consistently significant at the 1% level. Further, as shown in Table 7.10, the estimated WTP of respondents who indicated themselves to be informed about climate change, concerned about climate change, and convinced of the anthropogenic nature of climate change was found to be higher than that of respondents who indicated their disagreement on any one of these points. The preferred interval-data model found a mean WTP of R299 for respondents who were responded positively to all three climate-change related items, compared with R175 for respondents who responded negatively on one or more of these counts. This difference is also found in the results from the uncalibrated non-parametric model, which found a mean monthly WTP of R173 for respondents who agreed to all three climate change items, compared with R124 for respondents who did not agree with one or more of these items.

This result is again expected – respondents who do not believe that the CO_2 emitted in the combustion of coal is a harmful pollutant face vastly less compelling incentives to pay for a product that replaces coal with renewables. The strong and significant positive relationship observed by all multivariate models suggests that WTP for green electricity is tightly linked to the perceptions and beliefs that respondents hold regarding climate change.

Table 7.10: WTP estimates and beliefs related to climate change

	Non-Parametric WTP		Interval-Data Model	
	Yes	**No**	**Yes**	**No**
Respondent is informed about Climate change	R 154.41	R 127.17	R 258.93	R 169.86
Respondent is concerned about Climate Change	R 153.75	R 105.70	R 247.35	R 139.99
Respondent believes Climate Change to be anthropogenic	R 164.08	R 112.65	R 267.31	R 160.39
Respondent is informed and concerned about man-made climate change.	R173.26	R124.21	R299.27	R175.43

Respondent attitudes towards renewable energy technologies were also found to be strong predictors of WTP. The perception that the Western Cape's 15% green electricity target is a worthwhile goal for government was found to be positively related to WTP in all models, and this relationship was highly significant in all cases. The preferred interval-data model estimates a change from 0 to 1 in this binary indicator variable to be associated with an increase of around R72 in monthly WTP.

The belief that getting more of our electricity from renewable sources is a good idea was found to be a positive predictor of WTP in all models, and this relationship was consistently significant at 10% or better.

Confidence in renewable energy technologies was found to be a positive predictor of respondent WTP by all models, though the significance of this relationship varies widely, between single-bounded (finding: not significant) and double-bounded (finding: significant) models. Respondents who indicated their belief that renewables like wind and solar power will be major sources of electricity in the future were found to have higher WTP. Moreover, nearly 60% of the respondents who indicated their explicit disagreement with this statement also declined the offer to purchase both of the green electricity products presented to them in the hypothetical market. Again, this result is intuitively reasonable – respondents who do not believe that renewables will play a large role our future generation-mix have little to gain from subsidising their development in the present. It is also likely that explicit disagreement with the notion that renewables will be a major future energy source is indicative of a larger set of cynical beliefs related to the environment and environmentalism.

Table 7.11: Non-parametric WTP and Interval Data WTP estimates by attitudes to renewable energy

	Non-parametric WTP		Interval-Data Model	
	Agree	**Disagree**	**Agree**	**Disagree**
The WCPG's green electricity target is a worthwhile goal for government	R 159.94	R 104.27	R 265.82	R 122.19
Wind and Solar power will be major sources of electricity in the future	R 159.46	R 107.78	R 260.70	R 138.67
Getting more of our electricity from renewable sources is a good idea	R 154.82	R 77.27	R253.48	R55.57

Finally, the perception that nuclear power is a clean and safe source of electricity was found to be negatively related to WTP, but this relationship was not statistically significant in any of the estimated models. This result is as expected – though preferences regarding nuclear power may moderate a respondent's demand for green electricity through its effects as a substitute or complement, it is unlikely to be a major determinant of WTP. Support for nuclear power and support for green electricity can happily coexist, if both are motivated by the desire to see CO^2 emissions from coal combustion reduced.

The data collected for environmental norms were found to be too homogenous to detect the differences of interest amongst respondents. This variable was found to be an insignificant contributor to the multivariate model, and so was excluded from the analysis.

7.6.3: Behavioural Variables

In general, the behavioural variables included in this model fared poorly as predictors of WTP. Though participation in earth hour and the possession of a solar geyser were both found to be positively related to WTP, only the latter relationship was found to be significant as a predictor of respondent WTP.

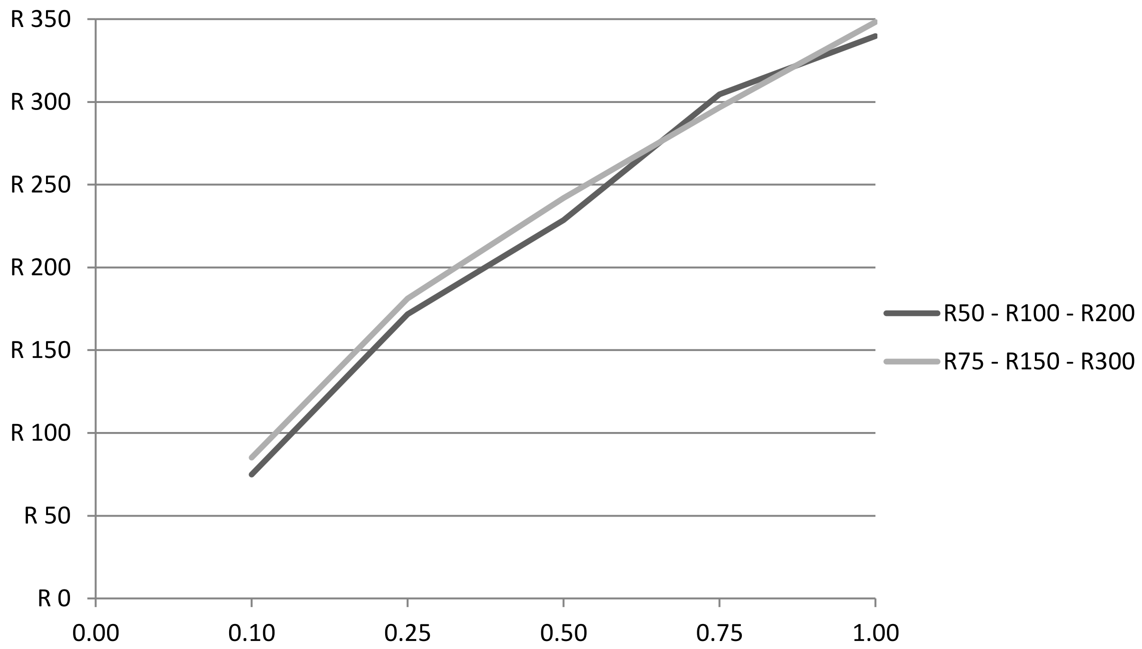
This result is intuitively sensible – whilst participation in an event like earth hour is certainly indicative of *some* pro-environmental sentiment, the sincerity and intensity of this sentiment is unclear. Indeed, for all its noble and lofty rhetoric, participating in earth hour requires no more than to substitute candles for electric lighting for one single hour per year. That this should serve as a weak predictor of willingness to voluntarily pay premium prices for green electricity is unsurprising. By contrast, the purchase of a solar water heating system entails a fairly large investment in renewable energy technologies, which thus indicates a far greater commitment to environmental preservation, as well as a vote of confidence in the effectiveness of such technologies as a substitute for conventional grid electricity and a cost-saving measure. Results from the preferred double bounded interval-data model showed possession of a solar water heating system to be associated with an increase of R81.74 in expected WTP.

The data collected for household recycling was found to be an insignificant contributor to the multivariate models, and so was excluded from the analysis.

7.6.4: Bid Values - Testing for Starting-Point Bias

A final factor for consideration as an explanatory variable is the vector of bid values presented to the respondent in the hypothetical market. Two versions of the survey were used by this study, differing only in the bid vectors they presented. As discussed in Section 6.4.2, these were the R50 - R100 – R200 and R75 - R150 – R300 bid vectors. To test for starting-point biases, the WTP distributions produced for these groups were compared.

The estimates of WTP produced by the interval-data model found mean values of R224.30 and R232.73 for respondents in the R100 and R150 initial-bid groups respectively, whilst the corresponding median WTP values were R228.66 and R241.96. On average, estimated WTP values were 6% higher amongst respondents presented with the higher initial bid. The WTP data does thus indicate the presence of starting point effects. However, the similarity between the mean WTP values for both bid vectors, and the close correspondence between cumulative WTP distributions shown in Figure 7.12 indicate that these starting-point biases are negligible in magnitude.



<u>Figure 7.12:</u> Cumulative distribution of Interval-data Model WTP estimates by bid vector

Chapter Eight: Policy Implications
What do these WTP estimates mean in practice?

Chapter 8 concludes the analysis of WTP for green electricity presented in this thesis with a context-laden discussion of the estimation results and their policy implications.

The ultimate motive for seeking to value the demand for green electricity products from household consumers is to ease the job of public officials tasked with determining the optimal mix of investments in electricity generation technologies. Chapter 8 contains three sections, each of which seeks to answer an important question in this regard. Section 8.1 examines the level of annual green electricity consumption which could be supported by the aggregate WTP values estimated in this study. Section 8.2 estimates the quantity of new renewable electricity capacity that would be required to supply the estimated household demand. Finally, Section 8.3 compares the aggregate WTP estimates produced by this study with the predicted cost of attaining the Western Cape's 15% green electricity target, and concludes by examining the policy implications of the results.

The analysis presented here makes use of the results from the preferred upper bound (interval data model) and lower-bound (non-parametric model – responses calibrated at 70%) estimation models, alongside the aggregate WTP values obtained for the population of 460 448 upper-middle income households.

8.1: What level of annual green electricity consumption could be supported by the aggregate WTP values estimated in this study?

Two possible prices for green electricity are considered when calculating the quantity of green electricity output that the estimated aggregate WTP could purchase.

The first of these measures is taken from the price at which the City of Cape Town sells green electricity certificates. All output produced by the Darling Wind Farm is supplied to the City of Cape Town, who then sell it to business consumers through a tradable green-electricity certificates system. Certificates were priced at 25.44c/kWh for 2011/2012 (City of Cape Town, 2012), which corresponds to a price of R254 400 per GWh of green electricity consumed. The second possible measure is taken from the difference in price between the wholesale price at which Eskom supplies electricity (61c/kWh for 2012/2013), and the tariffs paid to wind power producers participating in the second round of the REFIT process (103c/kWh). These figures collectively imply a cost premium of 42c per kWh (NERSA, 2012a; NERSA, 2012b). This corresponds to a price of R420 000 per GWh of green electricity consumed.

Table 8.1 presents the aggregate monthly and annual WTP for green electricity alongside the quantity of green electricity output that this aggregate WTP could purchase annually.

Table 8.1: Aggregate WTP estimates and green electricity output

	Aggregate Monthly WTP	Aggregate Annual WTP	Annual green electricity consumption	
			City of Cape Town Price: R254 400/GWh	*REFIT-tariff Price: R420000/GWh*
Double-bounded Interval Data Model	R 105.9 million	R 1 270 million	4994 GWh	3025 GWh
Non-Parametric Model (responses calibrated at 70% confidence)	R 31.1 million	R373.8 million	1469 GWh	890 GWh

As Table 8.1 shows, the aggregate WTP estimates from the interval-data model suggest that upper-middle income households would voluntarily purchase 3000-5000 GWh of green electricity per year. However, as discussed in Section 6.4.4, it is considered very likely that the estimates from this upper-bound model overstate true WTP. The aggregate WTP values estimated by the highly-conservative lower-bound WTP model (using responses calibrated at 70% confidence) may provide more realistic prediction of the likely scale of green electricity purchases. This model suggests that households would purchase a more modest total - around 900-1500 GWh annually.

8.2: How much new renewable electricity capacity would be required to produce this level of green electricity output?

The amount of new green electricity generation capacity that would be required to meet this demand is calculated using figures taken from the Western Cape Provincial Government's 2010 White Paper on Sustainable Energy. The planning scenario used in this document indicates that 832 MW of green-electricity generation capacity would be required to produce the targeted green electricity output of 2650GWh per year. This corresponds to an average annual output of 3.2GWh of green electricity per 1 MW of generation capacity.

Table 8.2 shows the total generation capacity required to supply the forecasted household demand for green electricity presented in Table 8.1. Alternatively, this could be considered as the quantity of green electricity generation capacity that the estimated annual WTP could support.

Table 8.2: Green electricity output that could be supported by aggregate WTP estimates

	Aggregate Annual WTP	***City of Cape Town Price: R254 400/GWh***		***REFIT-tariff Price: R420000/GWh***	
		Annual green electricity consumption	Required Generation Capacity	Annual green electricity consumption	Required Generation Capacity
Double-bounded Interval Data Model	R 1 270 million	4994 GWh	1568 MW	3025 GWh	950 MW
Non-Parametric WTP model (70% calibration)	R373.8 million	1469 GWh	461 MW	890 GWh	280MW

The generation capacity that could be supported by the voluntary green electricity purchases of households is thus in the range of 280-1600 MW. This is the equivalent of 50-300 times the capacity of the Darling Wind Farm.

8.3: How do the aggregate WTP estimates produced by this study compare with the cost of attaining the Western Cape's 15% green electricity target?

An estimate of the expenditure required to attain the Western Cape Provincial Government's 2650GWh green electricity output target is presented in Table 8.3.

Table 8.3: Cost of attaining the Western Cape's 2650GWh green electricity target

	Price (ZAR/ MWh)	Required Spending per year	Required spending per month	Monthly payment (Households pay 100%)	Monthly payment (Households pay 28%)
Certificate Price	R250	R 662.5 million	R 55.2 million	R 119.90	R33.32
Tariff difference	R420	R1113 million	R 92.7 million	R201.43	R56.40

Taking the current price of the City of Cape Town's certificates as a guide, selling the targeted annual green electricity output of 2650GWh would require R662 500 000 in spending per year, or R55 208 333.33 per month. This corresponds with a required mean spending of R119.90 per month for each of the 460 446 upper-middle income Western Cape households, if households were to bear the full burden of supporting the green electricity target. If, instead, the tariff difference is taken as the appropriate measure, R1.113 billion of spending is required each year, which comes to R92.7million per month. If the target were only supported by household spending, this would require a monthly payment of R201.43 per upper-middle income household.

However, households account for only around 28% of the total electricity consumption that occurs within the province, and could not be fairly expected to bear the full cost of attaining the target. Using this figure as the basis for a pro-rata calculation reduces the required monthly payment per household to R33.32 at the tradable certificate price, or R56.40 at the tariff-difference price.

The results of this estimation thus indicate that, regardless of the cost measure chosen, upper-middle income Western Cape households are willing to purchase a disproportionately large share of the targeted 2650GWh of green electricity output. The mean WTP value estimated by the upper-bound interval-data model is R228/month. Even if the more conservative 'tariff difference' price is used, this is about 12% greater than would be required for the green-electricity target to be fully funded by household contributions (R201/month), and around four times the contribution required (R56/month) if households only pay their fair share of 28%. Even the lower-bound estimate of mean WTP produced by the 70% calibrated Non-parametric model (R68/month) exceeds the high-price pro-rata contribution (R56/month) by almost 20%.

Thus, even by the most conservative interpretations, the results of the contingent valuation undertaken in this study indicate the existence of strong demand for green electricity products amongst Western Cape households. Further, the speculation that this demand could meaningfully contribute to the funding of the 15% green electricity target is strongly confirmed.

Chapter Nine: Conclusion

Trends in Western Cape Green Electricity Valuation Studies

This study set out to examine the demand for green electricity amongst Western Cape households, so as to update and enhance the information available to policymakers. This study now concludes by comparing the results obtained in this study with those obtained by the prior assessments undertaken by A.C. Nielson (2002) and Oliver *et al.* (2011). This comparison seeks to provide a loose examination of some relevant trends in the South African green electricity market. Unless otherwise stated, 'the WTP estimates this study' refer to those produced by the double-bounded interval data model. This model is considered most suitable for comparisons with Oliver *et al*. (2011) and A.C. Nielsen (2002), as response calibration was not used in either of these studies.

Methodological differences make comparisons of the results obtained from these three studies imperfect. However, the results from these studies show a number of clear trends.

Perhaps most notable of these trends is the manner in which the likelihood of Western Cape households expressing their intent to purchase green electricity products has been increasing over time. The 2002 study by A.C. Nielsen found 31% of respondents to be willing to pay a premium of 23c per kWh, whilst 24% indicated that they would be willing to pay a higher premium of 31c/kWh. In the 2007-8, survey conducted by Oliver (2009), 42% of respondents indicated that they would be to be willing to purchase green electricity, and found the mean price-premium reported by respondents to be around 26%, or 15c/kWh.

By contrast with these results, this study finds that nearly 80% of respondents report willingness to purchase a green electricity product, and the mean WTP value produced by this study was the preferred interval-data mean WTP value was R227, which corresponds with a price-premium of about 31%. There is thus evidence of an increasing trend in the predicted rates of adoption of green electricity products.

However, this comparison may be somewhat misleading, as this study restricted its attention to upper-middle income households, whilst Oliver *et al.* (2011) sought a more broadly representative sample of electrified households. Thus, to make these results more appropriate for comparison with AC Nielsen (2002) and Oliver *et al.,* (2011), the 515 444 electrified lower-income Western Cape households must be reintroduced to this analysis. As per the argument made in Section 4.1, these households are assumed to have an effective WTP of zero. When only upper-middle income households are considered the results of this study find mean household WTP to fall in the range R67.65 – R227.76. However, when the lower-income households are included as described, this corresponds to a range of far lower mean WTP values: the lower-bound estimate is R 31.92, and the upper-bound is R107.46. Further, the adoption rate predicted for this wider population is only 37.5%.

Thus, with some adjustments, the adoption rates and mean WTP values from this study are broadly comparable with the 42% and R117.67 found by Oliver *et al.* (2002). Further, the results of this study indicate that aggregate WTP for Western Cape households lies in the range of R31.1 million – R105.9 million per month. Though it does lie at the low end of the range, this is consistent with the aggregate value of R39 million per month estimated by Oliver (2009). Again, these comparisons are highly imperfect due to the different assumptions made regarding the WTP of poor households. Thus, although the estimation models in this study do find higher values of mean household WTP than Oliver (2009), it is difficult to conclude with confidence that mean household WTP has increased.

If the upwards trend observed in mean WTP values and adoption rates are taken to be valid, they are most convincingly explained with reference to an increase in the number of people reporting familiarity with, and favourable perceptions of, renewable energy.

The early assessments of household WTP for green electricity both found very low awareness of renewable energy technologies amongst Western Cape residents – only 14% of the AC Nielsen (2002) and 44% the Oliver (2009) samples reported familiarity with green electricity and renewable energy technologies. By 2012, this had risen sharply to 77%. A similar increasing trend was noted in the reported confidence in the potential for renewable energy technologies as major sources of electricity in the future. In 2002, 28% of sampled respondents reported this belief. By 2007-8, this had risen to 44%, and in this study, 72% of sampled respondents reported holding this belief. The trends observed in the responses to common covariates in these studies are summarised in Table 9.1.

<u>Table 9.1:</u> Trends in Western Cape Green Electricity Valuation studies.

Study	**A.C. Nielsen (2002)**	**Oliver *et al.* (2011)**	**Results from this study**	**Trend:**
Survey administered	*2002*	*Late 2007-Early 2008*	*Mid-2012*	
Proportion of sample indicating positive WTP	0.31	0.42	0.79	Possibly Increasing
Knowledge of Climate Change	-	0.74	0.66	Decreasing
Concern Regarding Climate Change	-	0.87	0.82	Decreasing slightly
Belief that Climate Change is man made	-	0.87	0.64	Decreasing
Familiarity with Renewable Energy Technologies	0.14	0.42	0.77	Increasing
Confidence in Renewable Energy technologies	0.28	0.44	0.72	Increasing

The results observed for climate-change related attitudes in this study were inconsistent with the expected trend. It was anticipated that the prominence of climate-change-related stories in the media, would lead to an increase in the proportion of respondents who accept the scientific consensus that climate change is driven primarily by human activities, and that it is something worth being concerned about. However, the results obtained from the survey indicate the opposite of this. In 2007-8, 87% of respondents surveyed in the Oliver (2009) study indicated that they were concerned about climate change. However, the results for this study indicate that only 82% of respondents to this (2012) study are concerned about climate change. Of greater concern is the decline in the proportion of respondents who report their belief that human activities are a major contributor to climate change, which dropped from 87% in 2007-8 to 64% in 2012. Further, the proportion of respondents who indicated that they do not believe human activities to be major contributors to climate change nearly tripled, from 3% to slightly less than 9%. These observations suggest that something of a 'backlash' has taken place in the public perceptions of climate change, either due to a reversion to the mean, after having attained unsustainable popularity in the past, or as a result of climate-change fatigue inspiring apathy in many individuals.

<u>Summary of Findings</u>

In all, this study found upper-middle income Western Cape households to be broadly supportive of environmental preservation causes. This is indicated by the high levels of agreement protecting the environment is a legitimate human responsibility, and the large number of respondents who express concern regarding the effects of climate change. However, this support does not automatically translate into pro-environmental behaviours, and most respondents remain at least somewhat unsure of their willingness to purchase a green electricity product. Further, only 14% of the sampled households own a solar water heating system. This indicates that only a minority of the respondents to this survey have made use of the opportunity to invest in renewable energy technologies that are immediately available to them.

The high levels of support for green electricity observed amongst upper-middle income households indicate the existence of a large potential market for green electricity products in the future. Further, the highly significant positive relationships observed between attitudinal variables and WTP points to high potential returns to public initiatives that attempt to foster such attitudes by publicising and promoting information about the environmental benefits of using renewables and the costs that uncontrolled climate change could potentially impose on society.

<u>Recommendations for contingent valuation research</u>

This study also makes some interesting findings on the conduct of contingent valuation studies, primarily relating to survey administration, and the use of response calibration approaches.

The choice to administer the survey for this study at regional traffic licensing centres proved very successful. Public service offices are seldom used in contingent valuation studies, though they have many advantages as venues for survey administration. The queue at these venues provides a self-selected, asymptotically-representative sample of the upper-middle income population, and the typically long and tedious wait provides a unique window within which respondents are likely to be unusually willing to participate, and unusually attentive. The generally-representative nature of the sample obtained and the unusually low item non-response rates observed in the survey administration attest to these virtues. Thus, public services offices are strongly recommended as administration venues, as they present an easy, low-cost opportunity for administering a survey, without many of the participation biases common in intercept sampling.

Though it is not standard practice for contingent valuation studies to attach reported-certainty measures as a follow-up to dichotomous choice valuation items, the results obtained in this study clearly indicate the value of doing so. This is especially the case for hypothetical markets trading in voluntary-adoption goods, or in any cases where the responses elicited by dichotomous choice items are of questionable sincerity. The sincerity and strength of the agreement to purchase implied by a 'yes' response in a hypothetical market is likely to vary widely between respondents. Although these differences cannot simply be ignored, the appropriate technique by which they can be included and accounted for remains unclear. This line of enquiry represents an obvious frontier in the conduct of contingent valuation studies, and one worthy of significant further examination.

The importance of measuring and considering the level of confidence that respondents report in their hypothetical responses is vividly illustrated by the results from the various non-parametric WTP models. Changing the threshold value used in the response calibration process leads to large differences in the mean WTP values produced. The wide variation in respondent confidence observed in this study serves to illustrate the inadequacy of the standard approach, which regards all affirmative responses to be equally credible. Thus, follow-up items assessing respondent confidence in dichotomous-choice responses are strongly recommended for use in contingent valuation studies.

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Appendices

Appendix A: Survey Booklet

The booklet attached as Appendix A is the survey questionnaire used to gather data on respondent characteristics, and to present the hypothetical market.

Two versions are included. The first, 'Version A' is the low-initial bid survey booklet presented to respondents whose households purchased their electricity using a prepaid meter. The second, 'Version D' is the high-initial bid survey booklet presented to households who receive a monthly bill for their electricity use.

A_______

May 2012

This survey is part of a study being conducted in the Western Cape Province by the UCT School of Economics. This study looks at the way that electricity is produced and used in the Western Cape.

Participation in this study is completely voluntary, and you can withdraw at any time. Your answers will remain completely anonymous and will be published only in aggregate forms. The study will neither name you nor describe you individually.

Thanks for taking the time to fill this in!

South Africa has been in an electricity supply crisis since 2008. To prevent the return of load-shedding, several new power plants are needed. We must choose between coal burning power plants and renewable energy sources like wind or solar power.

Coal plants produce cheap and reliable electricity, but they damage the environment by using up water and emitting pollution. These plants emit CO_2, which causes climate change, and SO_2, which causes acid rain. Right now, about 90% of South Africa's electricity comes from coal.

The alternative is using renewable technologies that generate electricity from natural sources like the wind and sunshine. Electricity from renewables is more expensive than coal-power, but it's better for the environment because it doesn't use any water or produce pollution.

Electricity from renewable sources is called 'green' electricity.

Section 1

These questions are about your opinions. There are no right or wrong answers. Think carefully, and answer as honestly as you can.

1:	Do you consider yourself to be well informed about Climate Change'?	Yes	Unsure	No
2:	Are you familiar with renewable energy sources like wind and solar power?	Yes	Unsure	No
3:	Are you concerned about climate change?	Yes	Unsure	No
4:	Does your household take part in Earth Hour?	Yes	Unsure	No

Do you agree with the following statements?

5:	People have a moral responsibility to take care of the environment.	Agree	Don't know/ Neither	Disagree
6:	Getting more of our electricity from renewable sources like wind or solar power is a good idea.	Agree	Don't know/ Neither	Disagree
7:	Climate change is caused by humans.	Agree	Don't know/ Neither	Disagree
8:	Nuclear power is a clean and safe source of electricity.	Agree	Don't know/ Neither	Disagree
9:	Wind and solar power will be major sources of electricity in the future.	Agree	Don't know/ Neither	Disagree

Section 2

The next section contains questions about your household, and we understand that you may not be used to discussing some of these things. We ask these questions to get an overall statistical view of your community, not to find out more about you personally. All data will be published in aggregate forms only.

1:	Age:	________	Male	Female

2:	Which area or suburb do you live in?
	______________________________

3:	Does your household recycle any of the following wastes?				
□ Tins	□ Paper	□ Glass	□ Light bulbs	□ Plastic	□ Batteries

4:	How much does your household spend on electricity in an average summer month?	
□ Under R 200	□ R400 – R600	□ R800 – R1000
□ R200 – R400	□ R600 – R800	□ Over R1000

5:	What is your household's monthly (after-tax) income?	
□ Less than R10 000	□ R30 000 – R40 000	□ R60 000 – R70 000
□ R10 000 – R20 000	□ R40 000 – R50 000	□ R70 000 – R80 000
□ R20 000 – R30 000	□ R50 000 – R60 000	□ R80 000 – R90 000
		□ Above R90 000

6:	What is the highest educational qualification held by a member of your household?		
□ Some high school	□ Bachelors degree	□ Masters degree	□ PhD
□ Matric	□ Honours degree	□ Other tertiary qualification	
Please Specify:			

7:	Does your household have a solar panel or solar geyser?	□ Yes	□No

In 2010, the Western Cape became the first province in South Africa to set a green electricity target, aiming to produce 15% of the province's electricity from renewable sources by 2014.

The laminated information sheet attached to this survey explains the environmental benefits of achieving this target.

Please read the information sheet carefully before you answer the next questions.

8:	Do you think the green electricity target is a worthwhile goal?	□ Yes	□ Unsure	□ No
9:	Would you prefer a program that replaced coal with nuclear power, instead of wind-power?	□ Yes	□ Unsure	□ No

The new 100MW Sere wind farm near Vredendal is almost complete.
When Sere starts operating, the green electricity that it produces will be available for sale to households and businesses. By switching to green electricity, you can cut your household's carbon-footprint and support the development of our local wind-power industry.

From late 2012, people who don't mind paying a little more for their electricity will have the option of having their household or business supplied with electricity from these wind farms by signing their households up for *Green Power!*©

Signing up for *Green Power!*© costs R100 per month in addition to what you currently spend on electricity. In return for this, 400 units (kWh) of the electricity you use each month will be supplied from the new wind farms. To avoid the inconvenience of sharp changes in your meter balance, this fee is paid through small daily deductions. No physical change to your connection is needed, and your electricity supply will be as reliable as always..

All payments go into the *Green Power!*© fund, which can only be used to buy green electricity produced in the Western Cape. Accounts from the fund are publicly available, and are audited once a year. Just 1792 *Green Power!*© households can support a wind farm as big as the one in Darling.

When you answer the next questions, keep your budget constraint in mind.

1:	Will you sign up for *Green Power!*© when it is launched?								□ Yes	□No
2:	If you answered **Yes**, how sure are you that you will actually sign up?									
	□ 10%	□ 20%	□ 30%	□ 40%	□ 50%	□ 60%	□ 70%	□ 80%	□ 90%	□ 100%

If you answered YES to question 1, turn to the next page. If you answered NO, skip the next page and turn to page 7

If you said YES to question 1, answer the questions below. If you said NO to question 1, skip to the next page.

Signing up for *Green Power!*© is a convenient way for you to reduce your environmental impact, but some people want to do more. If you're passionate about protecting the environment, then you should consider signing up for the premium *Green Power Plus!* © package.

Signing up for *Green Power Plus!* © costs R200 per month in addition to what you currently spend on electricity. In return for this, 800 units (kWh) of the electricity you use each month will be supplied from the new wind farms.

Just 896 *Green Power Plus!* © households can support a wind farm as big as the one in Darling.

:	Will you sign up for *Green Power Plus!*© when it is launched?								☐ Yes	☐No
4:	If you answered **Yes**, how sure are you that you will actually sign up?									
	☐ 10%	☐ 20%	☐ 30%	☐ 40%	☐ 50%	☐ 60%	☐ 70%	☐ 80%	☐ 90%	☐ 100%

The End

Thanks for taking the time to complete this survey!

If you said <u>NO</u> to question 1 (page 5), answer the questions below

Our research shows that a lot of people support the green electricity target, but find the *Green Power!*© package too expensive, especially when the price of electricity is already rising.

If you support the green electricity target, but find *Green Power!* © too expensive, then you should consider *Green Power! Lite*©. This starter package is perfect for consumers who want to do their part to protect the environment without breaking the bank.

Signing up for *Green Power! Lite* © costs <u>R50 per month in addition to what you currently spend on electricity.</u> In return for this, 200 units (kWh) of the electricity you use each month will be supplied from the new wind farms.
Just 3584 *Green Power! Plus*© households can support a wind farm as big as the one in Darling.

3:	Will you sign up for *Green Power Lite!*© when it is launched?								☐ Yes	☐ No
4:	If you answered **Yes**, how sure are you that you will actually sign up?									
	☐ 10%	☐ 20%	☐ 30%	☐ 40%	☐ 50%	☐ 60%	☐ 70%	☐ 80%	☐ 90%	☐ 100%

5:	If you answered No to question 3, what are your reasons for this?

<u>*The End*</u>

<u>*Thanks for taking the time to complete this survey!*</u>

D_______

May 2012

This survey is part of a study being conducted in the Western Cape Province by the UCT School of Economics. This study looks at the way that electricity is produced and used in the Western Cape.

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Coal plants produce cheap and reliable electricity, but they damage the environment by using up water and emitting pollution. These plants emit CO_2, which causes climate change, and SO_2, which causes acid rain. Right now, about 90% of South Africa's electricity comes from coal.

The alternative is using renewable technologies that generate electricity from natural sources like the wind and sunshine. Electricity from renewables is more expensive than coal-power, but it's better for the environment because it doesn't use any water or produce pollution.

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3:	Are you concerned about climate change?	Yes	Unsure	No
4:	Does your household take part in Earth Hour?	Yes	Unsure	No

Do you agree with the following statements?

5:	People have a moral responsibility to take care of the environment.	Agree	Don't know/ Neither	Disagree
6:	Getting more of our electricity from renewable sources like wind or solar power is a good idea.	Agree	Don't know/ Neither	Disagree
7:	Climate change is caused by humans.	Agree	Don't know/ Neither	Disagree
8:	Nuclear power is a clean and safe source of electricity.	Agree	Don't know/ Neither	Disagree
9:	Wind and solar power will be major sources of electricity in the future.	Agree	Don't know/ Neither	Disagree

Section 2

The next section contains questions about your household, and we understand that you may not be used to discussing some of these things. We ask these questions to get an overall statistical view of your community, not to find out more about you personally. All data will be published in aggregate forms only.

1:	Age:	________	Male	Female

2:	Which area or suburb do you live in?
	______________________________

3:	Does your household recycle any of the following wastes?				
□ Tins	□ Paper	□ Glass	□ Light bulbs	□ Plastic	□ Batteries

4: How much does your household spend on electricity in an average summer month?		
□ Under R 200	□ R400 – R600	□ R800 – R1000
□ R200 – R400	□ R600 – R800	□ Over R1000

5:	What is your household's monthly (after-tax) income?	
□ Less than R10 000	□ R30 000 – R40 000	□ R60 000 – R70 000
□ R10 000 – R20 000	□ R40 000 – R50 000	□ R70 000 – R80 000
□ R20 000 – R30 000	□ R50 000 – R60 000	□ R80 000 - R90 000
		□ Above R90 000

6:	What is the highest educational qualification held by a member of your household?		
□ Some high school	□ Bachelors degree	□ Masters degree	□ PhD
□ Matric	□ Honours degree	□ Other tertiary qualification	
Please Specify:			

7:	Does your household have a solar panel or solar geyser?	☐ Yes	☐No

In 2010, the Western Cape became the first province in South Africa to set a green electricity target, aiming to produce 15% of the province's electricity from renewable sources by 2014.

The laminated information sheet attached to this survey explains the environmental benefits of achieving this target.

Please read the information sheet carefully before you answer the next questions.

8:	Do you think the green electricity target is a worthwhile goal?	☐ Yes	☐ Unsure	☐ No
9:	Would you prefer a program that replaced coal with nuclear power, instead of wind-power?	☐ Yes	☐ Unsure	☐ No

The new 100MW Sere wind farm near Vredendal is almost complete.

When Sere starts operating, the green electricity that it produces will be available for sale to households and businesses. By switching to green electricity, you can cut your household's carbon-footprint and support the development of our local wind-power industry.

From late 2012, people who don't mind paying a little more for their electricity will have the option of having their household or business supplied with electricity from these wind farms by signing their households up for *Green Power!*©

Signing up for *Green Power!*© costs <u>R150 per month</u> <u>in addition to your existing electricity bill.</u> In return for this, 600 units (kWh) of the electricity you use each month will be supplied from the new wind farms. No physical change to your connection is needed, and your electricity supply will be as reliable as always.

All payments go into the *Green Power!*© fund, which can only be used to buy green electricity produced in the Western Cape. Accounts from the fund are publicly available, and are audited once a year.

Just 1195 *Green Power!*© households can support a wind farm as big as the one in Darling.

When you answer the next questions, keep your budget constraint in mind.

1:	Will you sign up for *Green Power!*© when it is launched?	☐ Yes	☐ No

2:	If you answered **Yes**, how sure are you that you will actually sign up?									
	☐ 10%	☐ 20%	☐ 30%	☐ 40%	☐ 50%	☐ 60%	☐ 70%	☐ 80%	☐ 90%	☐ 100%

If you answered YES to question 1, turn to the next page.
If you answered NO, skip the next page and turn to page 7

If you said <u>YES</u> to question 1, answer the questions below. If you said <u>NO</u> to question 1, skip to the next page.

Signing up for *Green Power!*© is a convenient way for you to reduce your environmental impact, but some people want to do more. If you're passionate about protecting the environment, then you should consider signing up for the premium *Green Power Plus!*© package.

Signing up for *Green Power Plus!*© costs <u>R300 per month, in addition to your existing electricity bill.</u> In return for this, 1200 units (kWh) of the electricity you use each month will be supplied from the new wind farms.

Just 597 *Green Power Plus!*© households can support a wind farm as big as the one in Darling.

3:	Will you sign up for *Green Power Plus!*© when it is launched?									☐ **Yes**	☐ **No**
4:	If you answered **Yes**, how sure are you that you will actually sign up?										
	☐ 10%	☐ 20%	☐ 30%	☐ 40%	☐ 50%	☐ 60%	☐ 70%	☐ 80%	☐ 90%	☐ 100%	

<u>The End</u>
<u>Thanks for taking the time to complete this survey!</u>

If you said <u>NO</u> to question 1 (page 5), answer the questions below

Our research shows that a lot of people support the green electricity target, but find the *Green Power!*© package too expensive, especially when the price of electricity is already rising.

If you support the green electricity target, but find *Green Power!* © too expensive, then you should consider *Green Power! Lite*©. This starter package is perfect for consumers who want to do their part to protect the environment without breaking the bank.

Signing up for *Green Power! Lite* © costs <u>R75 per month in addition to your existing electricity bill.</u> In return for this, 300 units (kWh) of the electricity you use each month will be supplied from the new wind farms.
Just 2389 *Green Power! Plus*© households can support a wind farm as big as the one in Darling.

3:	Will you sign up for *Green Power Lite!*© when it is launched?								☐ Yes	☐ No
4:	If you answered **Yes**, how sure are you that you will actually sign up?									
	☐ 10%	☐ 20%	☐ 30%	☐ 40%	☐ 50%	☐ 60%	☐ 70%	☐ 80%	☐ 90%	☐ 100%

5:	If you answered No to question 3, what are your reasons for this?

<u>The End</u>
<u>Thanks for taking the time to complete this survey!</u>

Appendix B: Information sheet

The Western Cape has set a target of generating 15% of the electricity used in the province from renewable sources by 2014.

These things can be difficult to imagine....this should help you picture it.

To achieve the 15% target, we need to build new wind farms with a total capacity of 832MW. That's 160 times as much as the Darling wind farm.

These wind farms will produce 2650GWh of electricity per year – enough to supply 518 495 average Western Cape households.

The Darling Wind Farm

Investing in renewable energy:

- ✓ supports the development of local green industries
- ✓ reduces our reliance on depletable fossil fuels
- ✓ creates green jobs

Achieving the 15% target would reduce our reliance on coal-fired power plants, which helps protect the environment.

Every year, we would save 1.4 million tons of coal - enough to fill 14 826 of these 100-ton coal hoppers.

That would reduce our CO2 emissions by 2.5 million tons per year.

We'd also save 3.3 billion litres of fresh water each year – that's enough to fill 880 Olympic-sized swimming pools.

The 15% target is achievable, but only if we can find money to cover the up-front cost of buying wind turbines.

Around the world, green-minded businesses and households have helped to finance investments in renewable energy by switching over to green electricity, even though it does cost a bit more.

Survey Number:

Thanks for taking the time to complete the survey!

In order to provide the best possible service over the coming years, we need as much information as possible about electricity consumers' preferences.

Keep in mind that the *Green Power!*© products that were presented by the survey are hypothetical. South Africa's first large wind farms and solar plants are currently being built, but decisions are still being made about how best to market green electricity to consumers.

The information you provided will be kept strictly confidential, and won't be published in any way that describes or identifies you as an individual. Should you wish to withdraw from the study, you can do so at any time by sending an SMS quoting your unique survey number to 082 480 7091.

Good Morning Mr Visser

I'm a postgraduate student at the University of Cape Town. In conjunction with the School of Economics, I'm conducting a study about electricity in the Western Cape. The study seeks to examine the opinions that Cape Town consumers hold towards renewable energy sources like wind and solar power.

A few foreign studies similar to ours have used the waiting lines at their local Department of Motor Vehicles as a venue for sampling. If it's possible, we would like to use a similar approach in our study, by inviting members of the public to complete our survey whilst waiting in queues at Traffic Centres in and around Cape Town. The survey questions are not related to traffic centres in any way, but these lines do provide an excellent sample of Cape Town's electricity users. I've attached a copy of the survey document we'd like to use to this email.

I was put in contact with you by Mrs Joubert from the Fish Hoek traffic centre, who told me that you'd be the person who would need to approve such a request. Could you advise me on the proper process for obtaining the required permission?

Thanks for your time.
Regards,
Chris Harrison
0741175715

Survey version 1.docx
109K View as HTML Scan and download

Reply | Reply to all | Forward | Print | Delete | Show original

Fri, Mar 9, 2012 at 11:29 AM

Kelvyn Visser

<Kelvyn.Visser@capetown.gov.za>

To: "chris.harrison25@gmail.com" <chris.harrison25@gmail.com>
Cc: Sibongile Makhapela <Sibongile.Makhapela@capetown.gov.za>, Karel Dick <Karel.Dick@capetown.gov.za>, Nicky Michaels <Nicky.Michaels@capetown.gov.za>, Frank Lock <FrancisCharles.Lock@capetown.gov.za>, Heathcliff Thomas <Heathcliff.Thomas@capetown.gov.za>
Reply | Reply to all | Forward | Print | Delete | Show original

Dear Sir

Your requested was directed to the correct person and approval is hereby granted for you to conduct the survey at our testing centres.

I have sensitised all my Assistant Chiefs in charge of the various centres to make them aware of the survey and to inform the members of staff accordingly.

Kind regards

K T VISSER

DEPUTY TRAFFIC CHIEF: LICENSING AND LOGISTICS

CAPE TOWN TRAFFIC SERVICES

CELL: 0725511171

TEL: 0214068874

FAX: 0865760891

Kelvyn.Visser@capetown .gov.za

Appendix D: Stata Output

Models:

Single Bounded Models:

1: Logit (uncalibrated)

```
. logit R1 B1 income eduyears age fem   moregreenb cc nucsafeb solargeyser earthhourb refutureb tgtworthwhileb, robust

Iteration 0:   log pseudolikelihood =  -249.2172
Iteration 1:   log pseudolikelihood =   -208.741
Iteration 2:   log pseudolikelihood = -207.48307
Iteration 3:   log pseudolikelihood = -207.47723
Iteration 4:   log pseudolikelihood = -207.47723

Logistic regression                             Number of obs     =        400
                                                Wald chi2(12)     =      64.07
                                                Prob > chi2       =     0.0000
Log pseudolikelihood = -207.47723               Pseudo R2         =     0.1675
```

R1	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
B1	-.0087724	.0049852	-1.76	0.078	-.0185433	.0009985
income	.130219	.0660576	1.97	0.049	.0007484	.2596896
eduyears	-.1036592	.0613543	-1.69	0.091	-.2239114	.016593
age	-.0247099	.0096572	-2.56	0.011	-.0436378	-.0057821
fem	.4545307	.252933	1.80	0.072	-.0412088	.9502701
moregreenb	.8148397	.4189034	1.95	0.052	-.0061959	1.635875
cc	.9680766	.2734594	3.54	0.000	.4321061	1.504047
nucsafeb	-.3255292	.3247257	-1.00	0.316	-.9619798	.3109215
solargeyser	.652452	.3975137	1.64	0.101	-.1266604	1.431565
earthhourb	.2736707	.2491622	1.10	0.272	-.2146783	.7620196
refutureb	.2089473	.2865662	0.73	0.466	-.3527122	.7706068
tgtworthwhileb	.8958986	.297447	3.01	0.003	.3129131	1.478884
_cons	1.759192	1.091365	1.61	0.107	-.3798441	3.898229

. est stats

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	400	-249.2172	-207.4772	13	440.9545	492.8435

Note: N=Obs used in calculating BIC; see **[R] BIC note**

Krinsky and Robb (95 %) Confidence Interval for WTP measures (Nb of reps: 5000)

MEASURE	WTP	LB	UB	ASL*	CI/MEAN
MEAN/MEDIAN	228.82	-301.14	777.94	0.0408	4.72

*: Achieved Significance Level for testing H0: WTP<=0 vs. H1: WTP>0
LB: Lower bound; UB: Upper bound

```
. margins, dydx(B1 income eduyears age fem   moregreenb cc nucsafeb solargeyser earthhourb refutureb tgtworthwhileb)

Average marginal effects                        Number of obs     =        400
Model VCE    : Robust

Expression   : Pr(R1), predict()
dy/dx w.r.t. : B1 income eduyears age 1.fem 1.moregreenb 1.cc 1.nucsafeb 1.solargeyser 1.earthhourb 1.refutureb 1.tgtworthwhileb
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
B1	-.0015073	.0008491	-1.78	0.076	-.0031714	.0001569
income	.0223745	.0112728	1.98	0.047	.0002803	.0444687
eduyears	-.0178109	.0104234	-1.71	0.087	-.0382403	.0026185
age	-.0042457	.0016207	-2.62	0.009	-.0074221	-.0010693
1.fem	.0783357	.0431067	1.82	0.069	-.006152	.1628233
1.moregreenb	.157399	.0880677	1.79	0.074	-.0152105	.3300085
1.cc	.1700323	.0467083	3.64	0.000	.0784857	.2615789
1.nucsafeb	-.0576291	.0588939	-0.98	0.328	-.1730591	.0578009
1.solargeyser	.1047409	.0584987	1.79	0.073	-.0099144	.2193963
1.earthhourb	.0475964	.0434837	1.09	0.274	-.0376301	.1328229
1.refutureb	.0367515	.0513888	0.72	0.475	-.0639688	.1374717
1.tgtworthwh~b	.1719862	.0602638	2.85	0.004	.0538714	.290101

Note: dy/dx for factor levels is the discrete change from the base level.

2:Probit (uncalibrated)

```
. probit R1 B1 income eduyears age i.fem   i.moregreenb i.cc i.nucsafeb i.solargeyser i.earthhourb i.refutureb i.tgtworthwhileb, robust

Iteration 0:   log pseudolikelihood =  -249.2172
Iteration 1:   log pseudolikelihood = -207.72098
Iteration 2:   log pseudolikelihood = -207.47256
Iteration 3:   log pseudolikelihood = -207.47236
Iteration 4:   log pseudolikelihood = -207.47236

Probit regression                               Number of obs     =        400
                                                Wald chi2(12)     =      72.36
                                                Prob > chi2       =     0.0000
Log pseudolikelihood = -207.47236               Pseudo R2         =     0.1675
```

R1	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
B1	-.0053081	.0029046	-1.83	0.068	-.011001	.0003848
income	.0778611	.0389596	2.00	0.046	.0015018	.1542204
eduyears	-.0594156	.03614	-1.64	0.100	-.1302486	.0114174
age	-.0145946	.0055922	-2.61	0.009	-.0255551	-.0036341
1.fem	.2597502	.1470744	1.77	0.077	-.0285103	.5480107
1.moregreenb	.5142403	.2463971	2.09	0.037	.0313109	.9971697
1.cc	.5641994	.1563637	3.61	0.000	.2577322	.8706666
1.nucsafeb	-.1853766	.193118	-0.96	0.337	-.563881	.1931277
1.solargeyser	.3851688	.2236811	1.72	0.085	-.0532382	.8235758
1.earthhourb	.1518811	.1464988	1.04	0.300	-.1352514	.4390135
1.refutureb	.1161319	.1686864	0.69	0.491	-.2144875	.4467512
1.tgtworthwh~b	.5295861	.1770126	2.99	0.003	.1826478	.8765244
_cons	1.017107	.6376111	1.60	0.111	-.2325874	2.266802

```
.
end of do-file
```

```
. margins, dydx(B1 income eduyears age fem   moregreenb cc nucsafeb solargeyser earthhourb refutureb tgtworthwhileb)

Average marginal effects                        Number of obs     =        400
Model VCE    : Robust

Expression   : Pr(R1), predict()
dy/dx w.r.t. : B1 income eduyears age 1.fem 1.moregreenb 1.cc 1.nucsafeb 1.solargeyser 1.earthhourb 1.refutureb 1.tgtworthwhileb
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
B1	-.0015529	.0008429	-1.84	0.065	-.003205	.0000992
income	.022778	.0113087	2.01	0.044	.0006133	.0449427
eduyears	-.0173818	.0104822	-1.66	0.097	-.0379265	.0031629
age	-.0042696	.0016028	-2.66	0.008	-.0074111	-.0011281
1.fem	.0762552	.0429143	1.78	0.076	-.0078553	.1603657
1.moregreenb	.1673661	.086266	1.94	0.052	-.0017121	.3364443
1.cc	.168788	.0460387	3.67	0.000	.0785539	.2590221
1.nucsafeb	-.0556628	.0592733	-0.94	0.348	-.1718363	.0605107
1.solargeyser	.1059853	.0569311	1.86	0.063	-.0055976	.2175682
1.earthhourb	.0448716	.0434993	1.03	0.302	-.0403854	.1301286
1.refutureb	.0346402	.0511603	0.68	0.498	-.0656322	.1349127
1.tgtworthwh~b	.170522	.0600423	2.84	0.005	.0528413	.2882027

```
. wtpcikr B1 income eduyears age fem   moregreenb cc nucsafeb solargeyser earthhourb refutureb tgtworthwhileb, reps(5000)

Krinsky and Robb (95 %) Confidence Interval for WTP measures (Nb of reps: 5000)
```

MEASURE	WTP	LB	UB	ASL*	CI/MEAN
MEAN/MEDIAN	227.13	-202.50	763.89	0.0358	4.25

```
*: Achieved Significance Level for testing H0: WTP<=0 vs. H1: WTP>0
LB: Lower bound; UB: Upper bound

. est stats
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	400	-249.2172	-207.4724	13	440.9447	492.8338

```
Note:  N=Obs used in calculating BIC; see [R] BIC note
```

```
. margins, dydx( B1 income eduyears age fem   moregreenb cc nucsafeb solargeyser earthhourb refutureb tgtworthwhileb)

Average marginal effects                          Number of obs   =        400
Model VCE    : Robust

Expression   : Pr(R1), predict()
dy/dx w.r.t. : B1 income eduyears age fem moregreenb cc nucsafeb solargeyser earthhourb refutureb tgtworthwhileb
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
B1	-.0015529	.0008429	-1.84	0.065	-.003205	.0000992
income	.022778	.0113087	2.01	0.044	.0006133	.0449427
eduyears	-.0173818	.0104822	-1.66	0.097	-.0379265	.0031629
age	-.0042696	.0016028	-2.66	0.008	-.0074111	-.0011281
fem	.0759891	.0425292	1.79	0.074	-.0073666	.1593448
moregreenb	.1504394	.0710564	2.12	0.034	.0111713	.2897074
cc	.1650547	.0439738	3.75	0.000	.0788677	.2512418
nucsafeb	-.0542313	.0563432	-0.96	0.336	-.164662	.0561994
solargeyser	.1126799	.0649388	1.74	0.083	-.0145978	.2399576
earthhourb	.0444323	.0426288	1.04	0.297	-.0391185	.1279832
refutureb	.033974	.0492225	0.69	0.490	-.0625002	.1304483
tgtworthwhileb	.1549287	.0498838	3.11	0.002	.0571583	.2526991

3: Logit Model (50% Certainty Calibration)

```
. logit R150 B1 income eduyears age i.fem   i.moregreenb i.cc nucsafeb i.solargeyser i.earthhourb i.refutureb i.tgtworthwhileb, robust

Iteration 0:   log pseudolikelihood = -270.74342
Iteration 1:   log pseudolikelihood = -230.77485
Iteration 2:   log pseudolikelihood = -230.55023
Iteration 3:   log pseudolikelihood = -230.54994
Iteration 4:   log pseudolikelihood = -230.54994

Logistic regression                             Number of obs   =        400
                                                Wald chi2(12)   =      61.90
                                                Prob > chi2     =     0.0000
Log pseudolikelihood = -230.54994               Pseudo R2       =     0.1485
```

R150	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
B1	-.0104328	.0047539	-2.19	0.028	-.0197503	-.0011153
income	.1702558	.0631338	2.70	0.007	.0465158	.2939958
eduyears	-.0305243	.0570214	-0.54	0.592	-.1422841	.0812355
age	-.021121	.0089556	-2.36	0.018	-.0386737	-.0035683
1.fem	.0014424	.2363198	0.01	0.995	-.4617358	.4646206
1.moregreenb	.8564227	.4284643	2.00	0.046	.0166481	1.696197
1.cc	.7615876	.2456364	3.10	0.002	.2801491	1.243026
nucsafeb	-.7246652	.324785	-2.23	0.026	-1.361232	-.0880984
1.solargeyser	.4510436	.3600937	1.25	0.210	-.254727	1.156814
1.earthhourb	.2638932	.2388659	1.10	0.269	-.2042753	.7320617
1.refutureb	.1800201	.2804192	0.64	0.521	-.3695913	.7296316
1.tgtworthwh~b	.7929977	.2921757	2.71	0.007	.2203438	1.365652
_cons	.5355929	1.023133	0.52	0.601	-1.469711	2.540897

.

```
. margins, dydx(B1 income eduyears age fem   moregreenb cc nucsafeb solargeyser earthhourb refutureb tgtworthwhileb)

Average marginal effects                        Number of obs   =        400
Model VCE    : Robust

Expression   : Pr(R150), predict()
dy/dx w.r.t. : B1 income eduyears age fem moregreenb cc nucsafeb solargeyser earthhourb refutureb tgtworthwhileb
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
B1	-.0020474	.0009104	-2.25	0.025	-.0038318	-.0002631
income	.0334126	.0120096	2.78	0.005	.0098742	.0569509
eduyears	-.0059904	.0111633	-0.54	0.592	-.02787	.0158892
age	-.004145	.0017073	-2.43	0.015	-.0074912	-.0007988
fem	.0002831	.0463776	0.01	0.995	-.0906154	.0911816
moregreenb	.1680723	.0826274	2.03	0.042	.0061255	.3300191
cc	.149461	.0461274	3.24	0.001	.059053	.239869
nucsafeb	-.142215	.0626828	-2.27	0.023	-.265071	-.019359
solargeyser	.088517	.0701534	1.26	0.207	-.0489813	.2260152
earthhourb	.0517888	.0465507	1.11	0.266	-.0394489	.1430266
refutureb	.0353288	.0550245	0.64	0.521	-.0725172	.1431748
tgtworthwhileb	.1556252	.0552819	2.82	0.005	.0472746	.2639758

```
. wtpcikr B1 income eduyears age fem   moregreenb cc nucsafeb solargeyser earthhourb refutureb tgtworthwhileb

Krinsky and Robb (95 %) Confidence Interval for WTP measures (Nb of reps: 5000)
```

MEASURE	WTP	LB	UB	ASL*	CI/MEAN
MEAN/MEDIAN	160.48	132.73	315.17	0.0134	1.14

```
*: Achieved Significance Level for testing H0: WTP<=0 vs. H1: WTP>0
LB: Lower bound; UB: Upper bound

. est stats
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	400	-270.7434	-230.5499	13	487.0999	538.9889

Note: N=Obs used in calculating BIC; see **[R] BIC note**

Calibrated Logit (70% certainty calibrated)

```
. logit R170 B1 income eduyears age fem   moregreenb cc nucsafeb solargeyser earthhourb refutureb tgtworthwhileb, robust

Iteration 0:   log pseudolikelihood = -265.13079
Iteration 1:   log pseudolikelihood = -234.94765
Iteration 2:   log pseudolikelihood =  -234.2131
Iteration 3:   log pseudolikelihood = -234.21011
Iteration 4:   log pseudolikelihood = -234.21011

Logistic regression                               Number of obs   =        400
                                                  Wald chi2(12)   =      42.71
                                                  Prob > chi2     =     0.0000
Log pseudolikelihood = -234.21011                 Pseudo R2       =     0.1166
```

R170	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
B1	-.0083678	.0046112	-1.81	0.070	-.0174055	.0006699
income	.1524866	.0585521	2.60	0.009	.0377265	.2672467
eduyears	.0053029	.0545878	0.10	0.923	-.1016872	.1122931
age	-.0064385	.0085981	-0.75	0.454	-.0232904	.0104134
fem	.1413738	.2287581	0.62	0.537	-.3069838	.5897314
moregreenb	.4085581	.5017576	0.81	0.415	-.5748687	1.391985
cc	.5199974	.2275086	2.29	0.022	.0740887	.9659061
nucsafeb	.0085568	.3154586	0.03	0.978	-.6097308	.6268443
solargeyser	.4022449	.3151428	1.28	0.202	-.2154236	1.019913
earthhourb	.4297237	.234309	1.83	0.067	-.0295135	.888961
refutureb	.6041227	.2852818	2.12	0.034	.0449806	1.163265
tgtworthwhileb	.7776304	.314933	2.47	0.014	.160373	1.394888
_cons	-1.849768	1.074916	-1.72	0.085	-3.956564	.2570281

```
.
end of do-file

.
```

```
. wtpcikr B1 income eduyears age fem   moregreenb cc nucsafeb solargeyser earthhourb refutureb tgtworthwhileb

Krinsky and Robb (95 %) Confidence Interval for WTP measures (Nb of reps: 5000)
```

MEASURE	WTP	LB	UB	ASL*	CI/MEAN
MEAN/MEDIAN	46.50	-347.84	365.80	0.2048	15.35

```
*: Achieved Significance Level for testing H0: WTP<=0 vs. H1: WTP>0
LB: Lower bound; UB: Upper bound
```

```
. est stats
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	400	-265.1308	-234.2101	13	494.4202	546.3093

Note: N=Obs used in calculating BIC; see **[R] BIC note**

```
. margins, dydx(B1 income eduyears age fem   moregreenb cc nucsafeb solargeyser earthhourb refutureb tgtworthwhileb)

Average marginal effects                          Number of obs   =        400
Model VCE    : Robust

Expression   : Pr(R170), predict()
dy/dx w.r.t. : B1 income eduyears age 1.fem 1.moregreenb 1.cc nucsafeb 1.solargeyser 1.earthhourb 1.refutureb 1.tgtworthwhileb
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
B1	-.0016854	.0009196	-1.83	0.067	-.0034877	.0001169
income	.0307134	.0113355	2.71	0.007	.0084963	.0529306
eduyears	.0010681	.0109938	0.10	0.923	-.0204793	.0226155
age	-.0012968	.0017247	-0.75	0.452	-.0046772	.0020835
1.fem	.0285773	.0462522	0.62	0.537	-.0620753	.11923
1.moregreenb	.0803041	.0951818	0.84	0.399	-.1062487	.2668569
1.cc	.1076429	.0474378	2.27	0.023	.0146665	.2006194
nucsafeb	.0017235	.0635362	0.03	0.978	-.1228053	.1262522
1.solargeyser	.0831057	.0662417	1.25	0.210	-.0467255	.212937
1.earthhourb	.0877043	.0481558	1.82	0.069	-.0066792	.1820879
1.refutureb	.11966	.0541393	2.21	0.027	.0135489	.2257711
1.tgtworthwh~b	.1536068	.0578688	2.65	0.008	.040186	.2670276

```
Note: dy/dx for factor levels is the discrete change from the base level.
```

Double-Bounded Models:

1: Bivariate Probit Model

```
. biprobit (R1 = B1 income eduyears age fem   moregreenb cc nucsafeb solargeyser earthhourb refutureb tgtworthwhileb) (R2 = B2 income eduyears age fem  moregreenb cc nucsafeb
> solargeyser earthhourb refutureb tgtworthwhileb), robust

Fitting comparison equation 1:

Iteration 0:   log pseudolikelihood =  -249.2172
Iteration 1:   log pseudolikelihood = -207.72098
Iteration 2:   log pseudolikelihood = -207.47256
Iteration 3:   log pseudolikelihood = -207.47236
Iteration 4:   log pseudolikelihood = -207.47236

Fitting comparison equation 2:

Iteration 0:   log pseudolikelihood = -270.37428
Iteration 1:   log pseudolikelihood = -246.64845
Iteration 2:   log pseudolikelihood = -246.60139
Iteration 3:   log pseudolikelihood = -246.60139

Comparison:    log pseudolikelihood = -454.07376

Fitting full model:

Iteration 0:   log pseudolikelihood = -454.07376
Iteration 1:   log pseudolikelihood = -451.21168
Iteration 2:   log pseudolikelihood = -443.00198  (not concave)
Iteration 3:   log pseudolikelihood = -442.91097
Iteration 4:   log pseudolikelihood = -442.52032
Iteration 5:   log pseudolikelihood = -442.48503
Iteration 6:   log pseudolikelihood =  -442.4833
Iteration 7:   log pseudolikelihood = -442.48329

Seemingly unrelated bivariate probit              Number of obs   =        400
                                                  Wald chi2(24)   =     129.29
Log pseudolikelihood = -442.48329                 Prob > chi2     =     0.0000
```

	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
R1						
B1	-.0070104	.0029451	-2.38	0.017	-.0127827	-.0012381
income	.0762648	.0376923	2.02	0.043	.0023893	.1501404
eduyears	-.0590187	.0370423	-1.59	0.111	-.1316204	.0135829
age	-.0134018	.0053378	-2.51	0.012	-.0238637	-.0029398
fem	.1924745	.1458871	1.32	0.187	-.0934589	.478408
moregreenb	.5063582	.2361962	2.14	0.032	.0434222	.9692943
cc	.5324076	.1539115	3.46	0.001	.2307466	.8340685
nucsafeb	-.1500091	.214683	-0.70	0.485	-.57078	.2707618
solargeyser	.3934641	.2190592	1.80	0.072	-.035884	.8228123
earthhourb	.1389473	.1443106	0.96	0.336	-.1438964	.4217909
refutureb	.1684841	.1641667	1.03	0.305	-.1532767	.4902448
tgtworthwhileb	.5447859	.177533	3.07	0.002	.1968277	.8927442
_cons	1.141364	.6044179	1.89	0.059	-.043273	2.326002
R2						
B2	-.0046214	.0012489	-3.70	0.000	-.0070692	-.0021736
income	.0637053	.0355424	1.79	0.073	-.0059566	.1333672
eduyears	-.0584486	.0328277	-1.78	0.075	-.1227896	.0058925
age	-.0029396	.0053367	-0.55	0.582	-.0133992	.0075201
fem	.141084	.1271172	1.11	0.267	-.108061	.3902291
moregreenb	.3614219	.2094376	1.73	0.084	-.0490682	.771912
cc	.3840375	.1406868	2.73	0.006	.1082966	.6597785
nucsafeb	-.2258813	.187421	-1.21	0.228	-.5932196	.1414571
solargeyser	.4507983	.1950477	2.31	0.021	.0685118	.8330848
earthhourb	.0647105	.1270668	0.51	0.611	-.1843358	.3137567
refutureb	.3967452	.1486716	2.67	0.008	.1053542	.6881361
tgtworthwhileb	.3156279	.1715613	1.84	0.066	-.0206259	.6518818
_cons	.7205843	.5420464	1.33	0.184	-.3418071	1.782976
/athrho	1.494802	.6934953	2.16	0.031	.1355761	2.854028
rho	.9042045	.1265034			.1347515	.9933837

```
Wald test of rho=0:                 chi2(1) =  4.64601     Prob > chi2 = 0.0311
```

```
. wtpcikr  B1 income eduyears age fem   moregreenb cc nucsafeb solargeyser earthhourb refutureb tgtworthwhileb, reps(100000)

Krinsky and Robb (95 %) Confidence Interval for WTP measures (Nb of reps: 100000)
```

MEASURE	WTP	LB	UB	ASL*	CI/MEAN
MEAN/MEDIAN	196.43	155.07	465.66	0.0084	1.58

```
*: Achieved Significance Level for testing H0: WTP<=0 vs. H1: WTP>0
LB: Lower bound; UB: Upper bound
```

```
. wtpcikr B2 income eduyears age fem  moregreenb cc nucsafeb solargeyser earthhourb refutureb tgtworthwhileb, reps(100000) eq(R2)

Krinsky and Robb (95 %) Confidence Interval for WTP measures (Nb of reps: 100000 and Equation: R2)
```

MEASURE	WTP	LB	UB	ASL*	CI/MEAN
MEAN/MEDIAN	235.33	208.08	296.73	0.0000	0.38

```
*: Achieved Significance Level for testing H0: WTP<=0 vs. H1: WTP>0
LB: Lower bound; UB: Upper bound
```

```
. est stats
```

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	400	.	-442.4833	27	938.9666	1046.736

```
              Note:  N=Obs used in calculating BIC; see [R] BIC note
```

Bid Only Model

```
. biprobit (R1=B1) (R2=B2), robust

Fitting comparison equation 1:

Iteration 0:   log pseudolikelihood = -271.71314
Iteration 1:   log pseudolikelihood = -270.14959
Iteration 2:   log pseudolikelihood = -270.14935
Iteration 3:   log pseudolikelihood = -270.14935

Fitting comparison equation 2:

Iteration 0:   log pseudolikelihood = -296.77596
Iteration 1:   log pseudolikelihood = -280.73301
Iteration 2:   log pseudolikelihood = -280.71895
Iteration 3:   log pseudolikelihood = -280.71895

Comparison:    log pseudolikelihood =  -550.8683

Fitting full model:

Iteration 0:   log pseudolikelihood =  -550.8683
Iteration 1:   log pseudolikelihood = -548.56326
Iteration 2:   log pseudolikelihood = -540.07552  (not concave)
Iteration 3:   log pseudolikelihood =  -539.9547
Iteration 4:   log pseudolikelihood = -539.67071
Iteration 5:   log pseudolikelihood = -539.66193
Iteration 6:   log pseudolikelihood = -539.66181
Iteration 7:   log pseudolikelihood = -539.66181

Seemingly unrelated bivariate probit              Number of obs   =        439
                                                  Wald chi2(2)    =       6.43
Log pseudolikelihood = -539.66181                 Prob > chi2     =     0.0402
```

	Coef.	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
R1						
B1	-.0060966	.0026322	-2.32	0.021	-.0112557	-.0009375
_cons	1.230876	.3218799	3.82	0.000	.600003	1.861749
R2						
B2	-.0038396	.001625	-2.36	0.018	-.0070244	-.0006547
_cons	.9270774	.3076881	3.01	0.003	.3240198	1.530135
/athrho	1.369449	.7150144	1.92	0.055	-.0319539	2.770851
rho	.8785664	.1631098			-.0319431	.9921909

```
Wald test of rho=0:                 chi2(1) =  3.66827    Prob > chi2 = 0.0555
```

```
Krinsky and Robb (95 %) Confidence Interval for WTP measures (Nb of reps: 5000 and Equation: R1)
```

MEASURE	WTP	LB	UB	ASL*	CI/MEAN
MEAN/MEDIAN	201.90	159.14	551.24	0.0104	1.94

```
*: Achieved Significance Level for testing H0: WTP<=0 vs. H1: WTP>0
LB: Lower bound; UB: Upper bound
```

Krinsky and Robb (95 %) Confidence Interval for WTP measures (Nb of reps: 5000 and Equation: R2)

MEASURE	WTP	LB	UB	ASL*	CI/MEAN
MEAN/MEDIAN	241.45	205.09	458.94	0.0082	1.05

*: Achieved Significance Level for testing H0: WTP<=0 vs. H1: WTP>0
LB: Lower bound; UB: Upper bound

2: Interval_Data Model

```
. doubleb B1 B2 R1 R2 income eduyears age fem moregreenb cc nucsafeb solargeyser earthhourb refutureb tgtworthwhileb

initial:       log likelihood =     -<inf>  (could not be evaluated)
feasible:      log likelihood = -58213.841
rescale:       log likelihood = -507.08707
rescale eq:    log likelihood = -507.08707
Iteration 0:   log likelihood = -507.08707  (not concave)
Iteration 1:   log likelihood = -471.24956
Iteration 2:   log likelihood = -465.60931
Iteration 3:   log likelihood = -452.46826
Iteration 4:   log likelihood = -452.38449
Iteration 5:   log likelihood = -452.38425
Iteration 6:   log likelihood = -452.38425

                                                  Number of obs   =        400
                                                  Wald chi2(11)   =      63.61
Log likelihood = -452.38425                       Prob > chi2     =     0.0000
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Beta						
income	12.79232	6.121993	2.09	0.037	.7934369	24.79121
eduyears	-11.28192	5.615379	-2.01	0.045	-22.28786	-.27598
age	-1.16005	.8586032	-1.35	0.177	-2.842882	.5227808
fem	29.29201	23.14943	1.27	0.206	-16.08003	74.66406
moregreenb	81.8886	38.65874	2.12	0.034	6.118869	157.6583
cc	80.56766	24.64027	3.27	0.001	32.27363	128.8617
nucsafeb	-36.88757	32.49643	-1.14	0.256	-100.5794	26.80426
solargeyser	81.7393	34.0772	2.40	0.016	14.94923	148.5294
earthhourb	15.67835	23.17175	0.68	0.499	-29.73743	61.09414
refutureb	60.60678	26.50763	2.29	0.022	8.65278	112.5608
tgtworthwhileb	72.48698	29.05922	2.49	0.013	15.53195	129.442
_cons	166.0976	84.70671	1.96	0.050	.0754676	332.1197
Sigma						
_cons	187.4384	14.29892	13.11	0.000	159.413	215.4637

```
First-Bid Variable:            B1
Second-Bid Variable:           B2
First-Response Dummy Variable: R1
Second-Response Dummy Variable: R2

.
end of do-file
```

. est stats

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
.	400	.	-452.3843	13	930.7685	982.6575

Note: N=Obs used in calculating BIC; see **[R] BIC note**

. summ DB1a

Variable	Obs	Mean	Std. Dev.	Min	Max
DB1a	400	227.7553	101.3353	-76.08937	473.8414