Fertility, Age and the Motherhood Wage Penalty in South Africa

Applied Economics Master's Dissertation

Catherine Torrington

TRRCAT001

Supervisor: Andrew Kerr

Abstract:

The difference in earnings between mothers and women without children is well-documented around the world. In developing countries, however, there has been far less research on the effect of fertility on wages for women. In this dissertation, I study the effects of fertility on wages for African women in South Africa. Using the National Income Dynamics Study (NIDS), I study the changes in wages experienced by mothers and non-mothers using panel data methods, as well as Ordinary Least Squares. I find that mothers in South Africa experience a small penalty, but this is not experienced equally for all mothers. Mothers with three or more children experience a greater penalty than mothers with fewer children, while the effects of having young children does not substantially affect the difference in earnings experienced by mothers. Since the majority of women in South Africa become mothers, a high proportion of the employed female population will experience a wage penalty in South Africa. Family- friendly policies, such as subsidized childcare, and flexible working options for mothers, would go a long way to reducing the wage penalty experienced by South African mothers.

1. Introduction

The gap in earnings between men and women is well-documented around the world. This disparity in earnings between men and women has been attributed to different factors, including differences in levels of education and work experience between men and women, discrimination against female employees, as well as differences in the types of jobs and industries that men and women typically occupy (Blau and Kahn, 2013). Another popular explanation is motherhood. Numerous studies have shown that having children is negatively correlated with women's earnings (for example, see Budig and England, 2001 and Grimshaw and Rubery, 2015). This disparity in earnings between women with no children, and women with children, is known as the motherhood wage penalty.

The motherhood wage penalty negatively effects societies worldwide. Since most women become mothers, a motherhood wage penalty hinders wage equality goals many societies are trying to implement, as well as wasting the economic potential of female workers (Grimshaw and Rubery, 2015). Policy and societal support are critical for working mothers, and the reasons that women choose to have children – and how this affects their ability to work – must be understood.

In the first part of this dissertation, I look at the links between fertility, age and labour market outcomes. Given that South Africa has one of the highest unemployment rates in the world, understanding when and why women choose to give birth is important for understanding the motherhood wage penalty. For example, if women choose to have children only once they are employed in a stable job, selection bias would affect the regression result, as the sample of women who have children would not be a random subset of the population.

In the second part of the dissertation, I study the motherhood wage penalty in South Africa. The few researchers who have studied the motherhood wage penalty in developing countries have found that the penalty tends to be greater in developing countries than in developed countries. This could be because developing countries have fewer mother-friendly policies in place that allow women to more work more easily while having children (such as subsidized childcare) or could be due to cultural norms.

If women are expected to be the primary caregivers for their children, and not to work out of the home, we would expect to see a greater penalty (Grimshaw and Rubery, 2015). Evidence for the effect of cultural norms on women's earnings was shown by Aguero et al., (2020), who studied the motherhood wage penalty in 21 developing nations. The authors found that mothers who had older daughters experienced a wage premium, compared with mothers who did not have older daughters. They suggested that daughters who can take on household chores free up time and energy for their mothers to seek employment outside the home. Thus, cultural practices and societal beliefs about where women should and should not work impact the extent of the wage penalty (Aguero et al., 2020).

In this dissertation, I contribute to the small but growing literature on the motherhood wage penalty in developing countries. I study the effect of children on women's earnings for black South African women using the National Income Dynamics Survey (NIDS) panel dataset. Although many previous researchers have documented female labour force participation and employment in South Africa (for example, see Casale, 2004 and Mosomi, 2019), to the best of my knowledge, there has only been one additional study on the motherhood wage penalty in South Africa. Magadla et al., (2019) used NIDS Wave 5 as a cross-section to study the effects of motherhood on earnings for African women in South Africa, using a Recentred Influence Function (RIF)-OLS regression analysis. The authors found that a penalty exists for women near the bottom of the income distribution, but that this penalty reduces for women higher up the income distribution. I build on the work of these authors by studying the wage penalty using panel data methods, alongside OLS. I find that a motherhood wage penalty does exist for African women in South Africa, but that this penalty is not experienced equally by all women. Women with fewer (1-2) children experience a substantially lower wage penalty than women with more (3+) children.

Along studying the motherhood wage penalty, I also look at the reasons that women choose to have children. In order to reduce the gap in earnings between mothers and non-mothers, women's fertility decisions must be properly understood. I find that South Africa is an outlier: despite extremely high unemployment rates, fertility levels in South Africa are similar to the fertility levels in other developing countries, although lower than fertility levels in many Sub-Saharan African countries. This is contrary to the economic theory which suggests that as employment increases, fertility decreases (Raymo and Shibata, 2017).

The rest of the dissertation is divided as follows: in Section 2, I review the existing literature on fertility and employment, and the motherhood wage penalty. In Section 3, I provide a description of the NIDS dataset. Section 4 includes an analysis of fertility and employment in South Africa. In Section 5, I use regression analysis to study the motherhood wage penalty in South Africa. Section 6 concludes.

2. Literature Review

2.1. Introduction

Traditionally, researchers have described the motherhood penalty as a wage penalty that women face when they become mothers. Most studies have compared the differences in wages between mothers and non-mothers (for example, see Budig and England, 2001 and Aguero et al., 2020). However, Kahn et al., (2014) argued that studying only the wage penalty does not give a full explanation of the impact of having children on women's career outcomes. Although differences in labour force participation decisions between mothers and non-mothers are not a *penalty* in the same way as wage differences are, they are still an important component of women's career outcomes, and motherhood is likely to affect the labour force participation decisions of women (Kahn et al., 2014). In South Africa, understanding the relationship between motherhood and labour force participation, as well as between motherhood and earnings, is particularly relevant given the extremely high unemployment rate. For example, only half of working-age women were participating in the labour market in the first quarter of 2021 (Statistics South Africa, 2021), and 34% of women were unemployed[1] (Statistics South Africa, 2021). Although many studies in South Africa have looked at the gender wage gap (for example, see Mosomi, 2019 and Bhorat and Goga, 2013), few studies have looked at the effect of motherhood, and the childcare burdens that follow, on women's labour force participation and earnings in South Africa. Understanding the effect of raising children and how this affects women's labour force participation, employment prospects and wages, is crucial to understanding the gender wage gap and how to lower it.

The rest of the literature review is structured as follows: Section 2.2 contains a description of the determinants of why women work, focusing on women in South Africa. In Section 2.3, I outline how women make decisions about fertility, and how this affects employment. In Section 2.4, I describe some of the previous research on the motherhood penalty, including explanations for the penalty, research in developing countries and econometric challenges in estimating the motherhood penalty. Finally, in Section 2.5, I outline my contribution to the literature.

2.2. Women's Labour Force Decisions

Women's labour force participation decisions have traditionally been harder to model than those of men. Women are often viewed as having a weaker attachment to the labour force (Barron et al., 1993) and fertility decisions, which do not impact men as they do women, often play a role in a woman's decision to enter the labour force or not.

[1] According to the strict definition of unemployment: women who were not working in the reference week, but who were available to work and who had actively looked for employment, or to start a business, in the past four weeks (Statistics South Africa, 2021).

Since the 1960s, women's labour force participation has increased substantially, particularly in developed countries (Killingworth and Heckman, 1987). The rise in female labour force participation in the developed world has been attributed to falling marriage and fertility rates, a weakening of the nuclear family (Clark and Withers, 2009) and increased government support for work-family policies that allow women to re-enter the labour force more easily after having a child (Blau and Kahn, 2013). A positive relationship between economic growth and female labour force participation in developing countries has also been observed: as economies develop, more women enter the labour force (Lechman and Kaur, 2015). However, the direction of causality is unclear, with other researchers finding that increased female labour force participation promotes economic growth in developing countries too (Ruiters and Charteris, 2020).

Before studying a wage penalty, it is crucial to understand who is working in a labour market, and why they choose to work. In South Africa, this is especially important, given the high rates of persistent unemployment (Statistics South Africa, 2021). Since a wage penalty analysis will, by definition, only include women who are employed, understanding which women enter the labour market, and which women find employment, is important.

In the next section, I look more broadly at women's labour force decisions in South Africa and consider factors that might influence women choosing to enter the labour force, such as the feminisation of the South African labour force, social grants, and migration. I then look at employment in South Africa and what influences the employment prospects of South African women.

2.2.1. The Feminisation of the Labour Force

In the 1990s, many South African women began to enter the labour force for the first time, in what Casale and Posel (2002) termed the "feminisation of the labour force" (Casale and Posel, 2002). The feminisation of the labour force is largely attributed to the end of the apartheid regime and the introduction of anti-discrimination and affirmative action laws implemented post-apartheid which allowed women, and especially African women, to enter the labour market more easily (Mosomi, 2019). Between 1995 and 2004, for example, African women's labour force participation increased from 35.6% to 47.4% (Ntuli and Wittenberg, 2013). By decomposing the changes in African women's labour force participation rates between 1995 and 2004, the authors estimated that up to 93% of the change in labour force participation for African women could be attributed to changes in laws and government policies, which allowed African women entry into the labour force, as well as and changes in human capital accumulation, with women achieving higher levels of education (Ntuli and Wittenberg, 2013).

Since the end of apartheid, the South African government has implemented an array of social grants, attempting to reduce inequality and poverty (van der Berg et al., 2010). For many women, access to social grants, either directly or indirectly, has some effect on their labour market outcomes. The next section discusses the social grant system, and its effect on women in South Africa in detail.

2.2.2. Social Grants

Since 1993, South Africa has extended its social grant scheme, aimed at the poorest and most vulnerable people in the country, as a method to reduce inequality and poverty (van der Berg et al., 2010). Social grants and cash transfer programs are controversial – some researchers have argued that they provide critical short and long-term relief from poverty, while critics claim that they encourage state dependency and, at best, provide only short-term relief from poverty (Leibbrandt et al., 2013). But researchers have found that social grants can provide long-term poverty relief if they promote human capital accumulation and encourage individuals to enter the labour market (Leibbrandt et al., 2013).

Given South Africa’s extensive grant system, high unemployment, poverty and inequality levels, much research has focused on the effectiveness of the grants in reducing poverty and inequality, and what extent grants have encouraged labour market participation. There is mixed evidence on the effect of social grants on labour supply in South Africa.

Social grants may increase the labour force participation rate of individuals if they cover the fixed costs associated with finding work – such as travel costs (Leibbrandt et al., 2013). Social grants also contain a gender dimension and may increase the labour supply of mothers if grants are used to cover costs of childcare services, allowing mothers to enter the labour force and search for work more freely (Leibbrandt et al., 2013). Since the Child Support Grant (CSG), for example, is awarded to the parent or guardian of a poor child, the grant is overwhelmingly awarded to women, usually the biological mother of the child (Tondini, 2017). Previous research has shown that access to the CSG increased the labour force participation and the probability of employment for young African mothers in South Africa (Eyal and Woolard, 2010). The researchers found that mothers were using the funds to cover the cost of school fees and day-care costs, evidence that some of the grant funding was being used to promote educational attainment for poor children (Eyal and Woolard, 2010).

For single mothers, who cannot rely on a partner’s wages, access to social grants may be even more important in promoting female labour supply. Tondini (2017) found that mothers whose youngest child is exposed to the grant are more likely to be formally employed rather than informally employed. Although he did not find any impact on overall employment, the shift from informal to formal employment was driven largely by unmarried mothers without a partner, suggesting that access to the CSG allowed single mothers the opportunity to search for formal jobs, rather than take on an informal job as a last resort (Tondini, 2017).

The other social grant that has received much attention is the Old Age Pension (OAP). The OAP is provided to pensioners (individuals aged 60 and older) who pass a means test. The evidence on the effect of the OAP on adult labour supply is mixed, with some researchers finding that the OAP is correlated with a reduction in prime adult labour supply (Abel, 2013), while other researchers identifying a positive correlation between labour supply and the OAP (Posel et al., 2006; Ardington et al., 2007). The effect of the OAP on labour supply seems to be linked to migration – a study that found a negative relationship between the OAP and labour supply considered only adults living in the household with the pensioner (Abel, 2013). However, studies that considered adult migration found that the supply of labour increased when pensioners received the OAP (Posel et al., 2006). This may be because parents find it easier to migrate to urban areas to look for work if they can leave their children with grandparents who are being supported by the OAP (Posel et al., 2006). For South African mothers, many of whom raise their children as single parents, this may be especially important. In the next section, I outline previous research on migration in South Africa, and how women in South Africa choose to migrate.

2.2.3. Migration

Temporary internal migration in South Africa has increased since the end of apartheid, driven largely by the rise in female labour force participation and female labour migration, particularly among rural African women (Posel, 2004). Although women are less likely to migrate if they are married, have young children, are employed in agriculture and are living with an employed man (Posel, 2004), the rise in female migration reflects changes in family structures and worsening economic conditions in South Africa (Posel, 2006). Many women, particularly women living in rural areas, may have migrated to look for work out of necessity, in order to support their families (Posel, 2006).

Women who want to migrate for work may be impeded from doing so if they have young children with them (Posel, 2004). However, researchers have found that the Old Age Pension is positively correlated with female labour force participation, especially when women migrate for work, and the pensioner is a woman too (Ardington et al., 2007; Posel et al., 2006). Mothers may feel more comfortable leaving their children with grandparents if they believe grandparents can support their grandchildren through social grant funding (Posel et al., 2006). Other types of grants, such as the Child Support Grant, have not been found to support female labour migration (Tondini, 2017) suggesting that the role of grandparents in providing childcare is particularly important for rural women's labour force participation (Posel et al., 2006).

2.2.4. Determinants of Female Employment

Although the feminisation of the labour force post-apartheid led to a large increase in female labour force participation, it did not lead to an equal increase in female employment. On the contrary, the feminisation of the labour force has often been classified by an increase in female unemployment and an increase in the number of women entering self-employment in the informal economy. These jobs are usually characterised as low-paying, insecure and having little protection (Casale and Posel, 2002). This pattern did not change in the first decade post-apartheid: in a later study, Branson (2006) found that although the labour force continued to expand post-apartheid, workers were not being sufficiently absorbed into the labour market. Many workers, and women in particular, continued to enter unemployment (Branson, 2006), suggesting that women were being "pushed" rather than "pulled" into the labour force, driven to enter the labour force to look for work out of necessity (Casale and Posel, 2002). This may have been due to increasing uncertainty surrounding employment, as unemployment rose for both men and women between 1995 and 2004 (Branson, 2006). Other researchers have suggested that a rise in female-headed households post-apartheid, the growing HIV/AIDS epidemic, and a reduction in remittances home, may have pushed women to enter the labour force and look for work (Casale and Posel, 2002).

More recently, researchers have shown that women's labour market outcomes remain precarious in South Africa. Although younger cohorts of women are more likely to participate in the labour force than older cohorts of women, women across all age categories are less likely to be employed than men of the same age (Mosomi, 2019). However, women's employment prospects have been helped by the increase in education available to them, as well as the skills-biased growth of the South African economy, which favours educated individuals (Mosomi, 2019). In this section, I discuss three determinants of employment prospects in South Africa in more detail: personal characteristics, education, and sectoral shifts in the economy.

2.2.4.1. Personal Characteristics

Despite affirmative action laws implemented in South Africa post-apartheid, race and gender remain significant in determining the probability of employment in South Africa. Black South Africans are less likely to find employment than South Africans from other race groups (Bhorat and Mayet, 2012), and female employment remains lower than male employment (Mosomi, 2019). Black South African women, consequently, are disproportionately affected and significantly less likely to be employed than men, and members of other race groups (Mosomi, 2019). Age is also significant for employment prospects in South Africa: youth unemployment remains high, with recent studies estimating that half of all youth (15–34-year-olds) in South Africa are unemployed[2] (De Lannoy et al., 2019). The persistently high levels of youth unemployment in South Africa have been attributed to slow job growth in the economy, early school-leaving, a lack of work experience and the fixed costs associated with job seeking, which disproportionately affect poor youth in the country (De Lannoy et al., 2019). Youth unemployment in South Africa is also higher for women than men, with early childbearing and domestic responsibilities affecting young women's ability to seek employment (De Lannoy et al., 2019). Since the end of apartheid, the government has invested enormous amounts of funding into improving the education system in South Africa (Spaull, 2013). Education is widely accepted to be key to increasing employment and earnings prospects for individuals (Anderson et al., 2001). In the next section, I explore the effect of education on employment in South Africa.

[2] According to the broad definition of unemployment, which includes discouraged workers (De Lannoy et al., 2019).

2.2.4.2. Education

As with many other countries around the world, the quality and quantity of education has been found to be positively associated with better economic outcomes, such as labour force participation and employment prospects, for South African adults (Anderson et al., 2001). This is especially true for individuals with higher levels of education, beyond matric (Anderson et al., 2001). Since the end of apartheid, there has been an increase in the average number of years (quantity) of education for African children. The gains in education for African women have been greater than for African men (Mlatsheni and Leibbrandt, 2001). This is in part due to higher enrolment rates in education for women: enrolment rates in primary, secondary and tertiary education are higher for women than for men in South Africa (Tijdens and Martin, 2009). For women, there is often an additional benefit to education: it may lower fertility and increases labour market participation and employment prospects (Mlatsheni and Leibbrandt, 2001).

However, although the quantity of education has increased dramatically in South Africa, the quality of education remains low, and varies considerably among schools (Branson et al., 2013). The overall quality of education in South Africa is weak (Bhorat et al., 2015), and this affects employment prospects. For example, one study found that for every 100 students who begin Grade 1 in South Africa, only 40 will pass matric, and only 12 will qualify for university (Spaull, 2013). High quality education is especially important in South Africa, where the post-apartheid economy has been biased towards skilled workers (Bhorat and Mayet, 2012). Thus, individuals with higher levels of education (quantity) as well as those who qualify for, and complete, tertiary education (quality), have significantly higher employment and earnings prospects in South Africa. In the next section, I provide an overview to the changes in the South African economy post-apartheid, and how these changes benefit highly skilled workers.

2.2.4.3. Sectoral Shifts in the Economy

Finally, although employment in South Africa has increased since the end of apartheid, the distribution of employment has been skewed across sectors (Bhorat et al., 2014). Before 1994, there was a high demand for skilled workers in South Africa, which has further increased post-apartheid (Bhorat et al., 2014). Jobs that are more automated, or routine, have seen sharp declines in employment, while jobs requiring face-to-face contact (such as social work) and high cognitive functioning (such as jobs requiring problem solving) have seen increases in employment (Bhorat et al., 2014). Researchers have found that 66% of the increase in employment in the South African economy has been concentrated in two sectors: financial and business services, and the retail industry (Bhorat and Mayet, 2012). Both industries form part of the ‘tertiary’ industries, demanding skilled workers. This has created a supply- demand mismatch for workers in the economy, with an oversupply of low and medium-skilled workers, and a dearth of highly skilled workers who, consequently, enjoy an employment premium (Branson et al., 2013).

Since the end of apartheid, women have made some gains in entering highly skilled occupations – in part due to achieving higher levels of education (Mlatsheni and Leibbrandt, 2001). However, female employment continues to lag behind male employment, and African men and women continue to be under-represented in managerial and professional occupations (Mosomi, 2019). For women, fertility and childcare continues to affect their labour market outcomes. In the next section, I discuss the interaction between fertility and women's decisions to work.

2.3. Fertility and Women's Labour Market Decisions

One of the most important factors in women's labour market decisions is fertility. Traditionally, fertility has been excluded from economic models describing labour market decisions. In the 1960s, economist Gary Becker changed this when he linked fertility and economic outcomes for the first time. Since then, researchers have found a negative relationship between fertility and economic opportunity, with fertility decreasing as female employment and opportunities for women to enter employment increases (Fang et al., 2013). This relationship is interesting to study in South Africa – a country where many women face a lack of employment opportunities, should they choose to enter the labour force. In the presence of low economic opportunities, understanding how women in South Africa make fertility decisions is important.

In this section, I begin by summarizing the theoretical backdrop to fertility, first theorized by Gary Becker. I then look at the interaction between fertility and economic opportunity, and then zoom in to look at fertility in South Africa, and how this affects women's decisions to enter the labour force.

2.3.1. Theoretical Framework

In his pivotal paper, Gary Becker (1960) connected fertility to economic outcomes for the first time (Becker, 1960). In his paper, he described children as an economic good, with parents choosing between quality and quantity of children. The more children a couple have, the fewer resources there are available for each child. Couples that have many children, consequently, invest in quantity (of children) over quality (Becker, 1960). On the other hand, couples that have few children have more resources to allocate to each child (such as better healthcare and education). These couples are investing in quality over quantity of children (Becker, 1960).

Although Becker's theory of the quantity-quality trade-off has been disputed (Doepke, 2015), economists have become more interested in understanding why people have children and how fertility affects the economic outcomes of families, and in particular, women. Since the 1960s, fertility levels around the world have been decreasing (Ewemooje et al., 2020), but developing countries, particularly in Sub-Saharan Africa continue to report high fertility levels (Bongaarts, 2015). In Sub-Saharan Africa, the average number of births per woman is 4.7 – the highest in the world (Novignon et al., 2019). Several reasons have been put forward by researchers to explain the continued high levels of fertility in the developing world.

In Sub-Saharan Africa, a strong positive correlation between poverty and fertility has been observed (Swartz, 2009). Countries with lower levels of poverty report lower levels of fertility too, suggesting a negative relationship between economic development and fertility. Falling fertility rates are usually seen as a sign of economic progress, as women achieve higher levels of education, have access to contraceptives, and are more empowered and able to make their own fertility decisions, independent of their husband or partner (Upadhyay et al., 2014).

Marriage is also positively correlated with fertility – women who are married have substantially higher fertility rates than unmarried women (Palamuleni et al., 2007). The age at which women first marry is also important for overall fertility: women who get married when they are young are more likely to have more children, than women who delay marriage (Palmuleni et al., 2007).

High levels of child and infant mortality have been linked to fertility in developing countries (Novignon et al., 2019; Westoff, 2010). In countries where child and infant mortality is high, parents may choose to have more children, either to replace children that have already died or may choose to have more children because of uncertainties surrounding children's survival (Novignon et al., 2019).

Furthermore, if children are seen as assets, couples may demand more children (Ahinkorah et al., 2020). This is particularly the case in developing countries, where children are expected to provide and care for parents as their parents age. In India, "son preference" has, in part, been attributed to the economic utility sons provide to their families (Mutharayappa et al., 1997). Sons are more likely than daughters to provide labour on a farm or in family businesses and are expected to support their parents during their old age (Mutharayappa et al., 1997). For many families in India, having more suns thus provides insurance for the future (Mutharayappa et al., 1997).

Education is widely accepted to be a key method to reducing the fertility rate of a country (Wodon et al., 2018). As women become more educated, their chances of using contraceptives and working outside of the home increases, both of which reduce fertility (Palamuleni et al., 2007). The effect of fertility on economic outcomes has also been studied empirically. A small but important body of research has focused on the relationship between economic opportunity and fertility. This is extremely important to understand as a background to the motherhood wage penalty, as it forms the basis of understanding who has children, and when, and how economic realities and fertility are related. In the next section, I outline some of the research on economic opportunity and fertility.

2.3.2. Economic Opportunity and Fertility

Economic models on fertility assume that children are costly, both in terms of money and time (Raymo and Shibata, 2017). With this assumption in place, a reduction in household income or employment for parents may produce a negative income effect that reduces fertility (Raymo and Shibata, 2017). On the other hand, since the opportunity cost of having children is high for employed women, a reduction in employment prospects for a woman may increase fertility, through a positive substitution effect (Raymo and Shibata, 2017). In other words, a reduction in employment prospects or economic opportunities for women may reduce the opportunity cost for having children and may lead to increases in fertility (Raymo and Shibata, 2017).

Policymakers and researchers around the world have identified economic opportunities for women as a key determinant of declining fertility (Simbanegavi, 2019; Obiyan et al., 2019; Raymo and Shibata, 2017). Researchers in Nigeria found that women's socioeconomic status (defined by her education level, work status and household wealth index) was significantly and negatively correlated with fertility. In Japan, researchers found that economic downturns – where many workers lost their jobs, or had their hours reduced – lead to a decrease in marriage rates for men and an *increase* in fertility for married women (Raymo and Shibata, 2017). Although the researchers found that both the negative income effect and positive substitution effect came into household's decision making, they found that the positive substitution effect – women substituting time spent in the labour force for time spent raising children – to be stronger (Raymo and Shibata, 2017).

A recent reduction in public sector jobs in Egypt allowed researchers to study fertility changes as economic opportunities for women reduced. The researchers found that, as female employment reduced in Egypt, fertility increased (Krafft, 2020). Policymakers in China have also pushed for increased economic opportunities for women as a key mechanism by which to reduce fertility rates (Fang et al., 2013).

Although many researchers have found a negative relationship between economic opportunity and fertility, with an increase in economic opportunities reducing fertility, understanding this relationship in South Africa is more complicated. South Africa has the lowest levels of fertility in Sub-Saharan Africa (Bongaarts, 2020), but also has one of the highest levels of unemployment in the world (Statistics South Africa, 2021). If women who have higher economic opportunities also have lower fertility rates, we would expect to see South African women having more children – and thus South Africa having a higher fertility rate. However, South Africa's low fertility rate, compared to the rest of Sub-Saharan Africa, combined with high unemployment and low employment opportunities for women makes this relationship between fertility and economic opportunity less clear. Thus, understanding why women choose to have children in South Africa, given the lack of economic opportunities for many women, is important.

2.3.3. Fertility in South Africa

Economic opportunity for women is not the only factor that affects fertility. The fertility rate of a country is also influenced by social and environmental factors. Many researchers have spent considerable effort deciphering how, and why, women choose to have children. South Africa has the lowest fertility rate in Sub-Saharan Africa. In 2016, the total fertility rate[3] (TFR) in South Africa was 2.6 births per woman (Statistics South Africa, 2020). Fertility remains of interest to researchers because of the relationship between fertility and economic outcomes.

South Africa's fertility rate decline has been attributed to many factors, including increased educational attainment (Mlatsheni, 2001), declining marriage rates (Garenne et al., 2001), and access to contraceptives (Palamuleni et al., 2007). A study conducted using the NIDS panel dataset (the dataset I will be using in this study) found that African

[3] Measured as the average number of children a woman in South Africa would have had by age 49 (Statistics South Africa, 2021).

women born in the late 1980s are expected, on average, to have two fewer children than African women born in the 1950s (Burger et al., 2012). The authors found that half of this decline in fertility could be explained by increased educational attainment, and declining marriage rates (Burger, et al., 2012). Another study conducted using the NIDS panel dataset found that girls who first gave birth as teenagers (between the ages of 15-18), were twice as likely to drop out of school as girls who did not first give birth as teenagers (Timaeus and Moulthie, 2015). This study shows the complicated relationship between fertility and education: while increased access to education has been associated with declining fertility, having children at a young age is also associated with declining educational outcomes.

Since the end of apartheid, educational attainment of women has increased, with younger cohorts of women being more likely to have completed at least 12 years of education, compared with older cohorts of women (Mosomi, 2019). Consistent with findings around the world, this increased educational attainment of women has been found to be important in explaining the reduction in fertility in South Africa (Mlatsheni, 2001; Burger et al., 2012; Ruiters and Charteris, 2020).

Marriage rates in South Africa have also declined continuously since the 1960s (Burger et al., 2012) and the age at which women first get married has increased (Garenne et al., 2001). Both factors have been found to be negatively correlated with fertility (Burger et al., 2012; Garenne et al., 2001). Part of this may be explained by social norms in South Africa – unmarried women report feeling less social pressure to have children, compared with married women (Burger et al., 2012).

Other researchers have found that women in South Africa control their fertility more carefully after having a child. Many mothers in South Africa raise their children without the support of their partners. 42% of children in South Africa are raised by their mothers only, without the support of their father (Statistics South Africa, 2021). Researchers have found that South African women control their fertility more after taking on raising children alone (Swartz, 2009). Researchers have also found that once women have given birth to their first child, their attitude to and use of contraceptives changes (Garenne et al., 2001). Most women in South Africa give birth in a clinic or hospital, where they have access to healthcare workers who can educate them on reproductive health and contraceptives. For women living in rural areas, this is often the first time they are in contact with healthcare workers (Garenne et al., 2001).

Finally, the type of contraceptives popular in South Africa also indicates how women in South Africa control their fertility – contraceptive methods such as the pill and injectables, as well as permanent methods such as sterilization, are most popular. This suggests that women are actively seeking to limit their fertility, rather than space out the births of additional children (Palamuleni et al., 2007). Burger et al., (2012), using the NIDS dataset, found that the decline in African women's fertility could only partly be explained by observed variables, such as increased educational attainment, and declining marriage rates (Burger et al., 2012). The authors speculate that part of the decline in fertility could also be explained by the changing social role of women in society, and the increased access to contraceptives, and control women had over their fertility (Burger et al., 2012).

Fertility is an important determinant of women's labour force participation and employment in South Africa (Ntuli and Wittenberg, 2013). Using the 2011 Census, researchers found that having one more child reduces the employment rate of African women by 4.9 percentage points (Ardington et al., 2015). The labour force participation rate of African women was also significantly affected: one more birth reduced the broad labour force participation rate (including discouraged workers) by 5.5 percentage points (Ardington et al., 2015).

In this section, I have outlined research which shows that, although women in South Africa are entering the labour force at greater rates, employment for women, and especially African women remains low. In this dissertation, I will be looking at the effect of having children on earnings. This requires women to be employed to be included in the sample. Thus, it is likely that my analysis on the motherhood wage penalty will include a minority of respondents – those women who are employed.

Furthermore, women in South Africa are more likely to be employed if they are better educated, older and have fewer children. The sample of women in my analysis will not be a representative sample of the female population in South Africa. Moreover, since having children is negatively correlated with employment, some women may drop out of employment (and therefore this analysis) as they have had additional children. In the next section, I discuss the motherhood wage penalty in detail. I begin by discussing previous research on the motherhood wage penalty, the reasons proposed for the penalty, and research done in developing countries. I then outline some of the econometric issues associated with measuring the motherhood wage penalty.

2.4. The Motherhood Wage Penalty

The feminisation of the labour force around the world has spurred further research into women's wages as well as labour force participation. Researchers have been interested in the differences in wages that mothers and non-mothers receive, known as the motherhood wage penalty. Although some researchers argue that the economic penalty that mothers face can be extended to include changes in occupation status and labour force participation (Kahn et al., 2014), most researchers have studied only the motherhood wage penalty – that is, the difference in earnings between mothers and non-mothers[4].

2.4.1. Explanations for the Motherhood Wage Penalty

There are many different, and often conflicting, explanations for why mothers earn less than non- mothers. In this section I provide an overview of some of the most popular explanations for the motherhood wage penalty. Firstly, some researchers argue that career breaks women are likely to take when they have a child, reduce their human capital accumulation and time spent working, which will affect wages (Kahn et al., 2014; Budig and

[4] Although the earnings penalty experienced by women is commonly referred to as a "wage" penalty in the literature, the earnings variable used by researchers in analysis is varied. Some researchers use weekly or monthly earnings, while other researchers use hourly wages. To ensure consistency with the literature, in the rest of this dissertation, I refer will refer to the difference in earnings – defined in the dissertation as the difference in monthly take home pay between mothers and non-mothers – as the motherhood *wage* penalty.

England, 2001). Mothers may also be more likely to seek "family-friendly" jobs (Staff and Mortimer, 2012; Posel and Muller, 2008), which allow for flexible working conditions, and which may be lower-paying. This 'reduced' work commitment accounts for the differences in wages between mothers and non-mothers. Other researchers argue that mothers may face discrimination from employers, who may stereotype them as being less committed workers (Berard and Correll, 2010), or that family structures play a role in women's wages, with married women being more likely to 'specialise' in raising children, while their husband 'specialises' in participating in the labour force (Becker, 1985; Killewald and Gough, 2013). Government policies in different countries may affect women's ability to work after having had a child. Mother-friendly policies, such as subsidized childcare, may allow women to re-enter the labour force more freely after having had a child (Grimshaw and Rubery, 2015). These explanations are discussed in more detail below.

2.4.1.1. Human Capital Differences

One of the most popular explanations for the motherhood penalty is that human capital accumulation over women's lifetimes differ markedly for mothers and non-mothers. Mothers may face a reduction in human capital investments when they take time off to look after their children, or after giving birth (Gangl and Ziefle, 2009), and motherhood may slow or reduce the incentive for mothers to accumulate human capital (Oesch et al., 2017).

Most researchers agree that human capital differences are important in explaining at least part of the difference in wages experienced by mothers and non-mothers. The cumulative time spent on human capital activities – including education, continuous employment, and on-the-job training – may reflect the productivity of workers in a competitive marketplace (Gangl and Ziefle, 2009). Thus, if mothers spend less time accumulating human capital, either through taking career breaks, or investing less in their education, we may expect their wages to be lower than those of non-mothers (Gangl and Ziefle, 2009). Empirical research suggests that this theory is at least partially true. Budig and England (2001) found that accounting for differences in education and on-the-job training could account for one-third of the wage penalty experienced by mothers in the United States. Staff and Mortimer (2012) studied the early career trajectory of women in Minnesota and found that the cumulative time mothers did not spend on human capital activities was the biggest determinant of the penalty experienced by young mothers (Staff and Mortimer, 2012).

In a longer study, Kahn et al. (2014) followed women in the US over their entire career lifetime and found that differences in human capital accumulation were important in explaining a large portion of the differences in earnings between mothers and non-mothers. This was especially the case for mothers with three or more children: accounting for differences in human capital reduced the motherhood penalty from 17% to 3% (Kahn et al., 2014). Finally, the reduction in human capital accumulation may affect mothers differently. Anderson et al., (2002) divided their cohort of American women into three mutually exclusive education groups (did not finish high school; completed high school with some college education; and college graduate) to study the differences in human capital accumulation by education group. They found that a wage penalty exists for mothers only in the better-educated cohorts, with the most highly educated women facing the highest penalty. 60% of the penalty faced by mothers in the 'completed high school' cohort could be explained by differences in human capital accumulation. For college graduates, only 20% of the penalty could be explained by the same difference in human capital accumulation (Anderson et al., 2002).

2.4.1.2. Mothers seek "Family-Friendly" Occupations

In an early paper, Becker (1985) compared married men and women and argued that specialized human capital, whereby men invested time and effort in the labour force and women invested time and effort in raising and caring for children, led to better outcomes for couples. Since mothers face the burden of raising children (and this requires a lot of time and effort), mothers who worked would exert less effort in the labour force, be less productive and, consequently, would earn lower wages (Becker, 1985). Becker's theory forms the basis of the argument that mothers, in an effort to balance work and family commitments, choose occupations that are easier to combine with motherhood – such as jobs that allow for flexible working hours and low demands for travel and weekend work (Budig and England, 2001). These jobs are also likely to be lower paying and less prestigious, and mothers are willing to trade wages for the 'family-friendliness' of the job (Budig and England, 2001).

However, Becker's theory that it is the *specialization of labour* between married men and women that causes women to select into "mother-friendly" occupations, or to move out of the labour force entirely, has come under criticism. A recent study found that, although married men in the United States do experience a wage premium when they get married, this does not happen at the expense of married women's wages. On the contrary, married women also experience a wage premium when they get married, although this premium is more modest than that of their male partners (Killewald and Gough, 2013). Furthermore, although the authors found a significant motherhood penalty for mothers in their sample, the penalty varied little between married and unmarried women, suggesting that specialization between married men and women was not the cause of the penalty experienced by married women (Killewald and Gough, 2013).

Nevertheless, mothers' selection into part-time work has been identified as a key strategy mothers use to reconcile work and family commitments (Budig and England, 2001; Gangl and Ziefle, 2009; Posel and Muller, 2008). Motherhood has been found to be positively correlated with the likelihood of women working part-time in the United States (Gangl and Ziefle, 2009), while in South Africa, women who reported to be living with children were found to be more likely to be employed in part-time work (Posel and Muller, 2008).

The potential for women to take career breaks, reduce their human capital accumulation and to select into less prestigious, lower-paying occupations once they have a child may also incentivise employers to discriminate against women. If employers believe that women are less dedicated to their careers, from an economic perspective, it makes sense for employers to promote and incentivise workers who they believe will continue to be productive workers in the future (Grimshaw and Rubery, 2015). Experimental research has found that mothers do experience discrimination, and that this may contribute to the lower wages that mothers receive.

2.4.1.3. Employer Discrimination

Employer discrimination against mothers may also affect wages. Labour economists tend to divide discrimination in two: “taste” discrimination, whereby employers may find it distasteful to hire mothers because of some unseen bias that they have towards mothers, and “statistical” discrimination, where employers assume that mothers will be less productive employees, and so choose to not hire them, or to hire mothers but pay them less. Previous experimental research has shown that mothers are perceived to be less committed to their job, and less competent (Benard and Correll, 2010). However, Benard and Correll (2010) performed an experiment to determine whether mothers who had “unimpeachable work credentials” - in other words, who had proven to be committed and capable, experienced negative stereotyping too. They found that these women were stereotyped as “cold”, “devious” and “selfish” compared to other types of workers. The authors speculate that by not fitting into the stereotype of a mother (warm and nurturing), highly competent and ambitious mothers are discriminated against too (Benard and Correll, 2010).

2.4.1.4. Government Intervention

Differences in policy and economic development between countries may also exacerbate the wage penalty. Studies from different countries report different levels – and determinants – of the motherhood wage penalty. Institutional differences between countries, such as the provision for subsidized or state- provided childcare services, may affect mother’s ability to participate in the labour force, and the types of jobs that they occupy (Gangl and Ziefle, 2009). A study on women born in the United States, the United Kingdom, and West Germany between 1950-1960 found that in each region, mothers experienced a different wage penalty, with different factors affecting the penalty (Gangl and Ziefle, 2009). For example, mothers in West Germany faced the highest penalty (between 16-18% per child), while mothers in the United Kingdom faced the lowest penalty (9% per child). Moreover, almost all of the penalty experienced by both mothers in the United States and United Kingdom could be explained by labour force behaviour differences between mothers and non-mothers (for example, differences in experience and time taken off work). However, labour force differences explained almost none of the wage penalty faced by mothers in West Germany (Gangl and Ziefle, 2009). Research also suggests that government policies and initiatives may become more important as economies develop and become more complicated (Grimshaw and Rubery, 2015).

2.4.2. The Motherhood Wage Penalty in Developing Countries

There is far less research on the motherhood wage penalty in developing countries. Grimshaw and Rubery (2015) argue that the motherhood wage penalty may be higher in developing countries because there are fewer institutional resources to help mothers, such as childcare facilities. On the other hand, informal childcare sources may be more readily available for mothers in developing countries, which could allow women to remain in the labour force more easily (Aguero et al., 2020). Researchers studying the motherhood wage penalty in low and middle-income countries found that mothers in low-income countries experience a wage premium if they have teenage daughters. The authors speculate that because daughters are expected to perform household chores along with their mother, having daughters, and thus more help with household chores, allows mothers to allocate more time to a career (Aguero et al., 2020). Given that most women become mothers, some researchers have expanded the motherhood wage penalty to measure the number of children a woman has given birth to. Aguero et al. (2020) used a continuous variable to measure how having additional children affect women's wages in developing countries. Following their work, I will do the same in this dissertation.

As with literature on developed countries, the extent, and reasons for the motherhood wage penalty in developing countries, varies. In Uruguay, for example, researchers estimate that mothers face a 19% wage penalty, which can be explained by differences in formal employment between mothers and non-mothers (with women being more likely to drop out of formal employment once they become mothers) and a reduction in work hours (Querejeta Rabosto and Bucheli, 2021). In contrast, researchers in Colombia found that mothers experience a much smaller, albeit significant, wage penalty of 1.73%. However, when the researchers controlled for differences in education, the wage penalty reduced substantially and became insignificant, leaving the researchers to conclude that there is "no evidence of wage discrimination against mothers in the Colombian labour market" (Gamboa and Zuluaga, 2013).

Finally, Magadla et al (2019) studied the motherhood wage penalty for African women in South Africa using Wave 5 of NIDS. The authors used unconditional quantile regressions to study the difference in wages between mothers and non-mothers at different points in the wage distribution. They found that a motherhood wage penalty exists for mothers at near the bottom of the wage distribution, and that part of this penalty cannot be explained by observed characteristics. The authors suggest that this could be due to social norms and behavioural characteristics that disproportionately affect women near the bottom of the wage distribution (Magadla et al., 2019). For women near the top of the wage distribution, they found that mothers enjoy a wage premium, especially if they work part-time and are married (Magadla et al., 2019). However, by using only cross-sectional analysis, the authors do not account for unobserved heterogeneity which could bias their results. If the groups of mothers and non-mothers in South Africa have differences which are not accounted for in the data, any difference in wages could be caused by these unobserved characteristics. In this dissertation, I will use both cross-sectional and panel data methods to study the wage penalty experienced by mothers.

2.4.3. Economic Challenges in measuring the Motherhood Wage Penalty

Estimating the motherhood wage penalty presents econometric challenges. In this section, I discuss three of the most common econometric challenges researchers face when studying the motherhood penalty: unobserved heterogeneity, spurious correlation, and selection into employment.

2.4.3.1. Unobserved Heterogeneity

Most researchers look at the wage penalty women experience when they become mothers, and so compare the wages of mothers to those of non-mothers. However, since most women do become mothers, it is more interesting to look at the effect of having children on women's wages. In this dissertation, following Aguero et al (2020), instead of using a dummy variable *mother* to indicate whether a woman is a mother or not, I will use a continuous variable, *kids,* indicating the number of children a woman has given birth to. Including *kids* as a continuous variable assumes that the penalty experienced by having an additional child is the same, regardless of the number of children a woman already has. Very simply, this could be done as shown by equation (1) below. In (1), *kids* is a continuous variable indicating how many children a woman has.

$$\log(wage)_i = \beta 0 + \beta 1(kids)_i + u_i \tag{1}$$

For this simple regression to be unbiased, we must assume that the zero conditional mean assumption holds:

$$E(u|x) = 0 \tag{2}$$

Equation (2) states that the expected value of the error term (u) is zero, given any value of the explanatory variable. This would be true only if none of the omitted variables in the error term affected the explanatory variable – in this case, the number of children a woman has (Wooldridge, 2015). Intuitively, this is unlikely to be true. There are likely to be many factors that affect both childbearing and earnings, including marital status, educational attainment, and household characteristics.

We can attempt to solve this problem by including observed characteristics into the wage regression. A Mincerian wage regression, where wages are a function of demographics, work experience, educational attainment and household characteristics has been used by researchers (see Budig and England, 2001) to study the motherhood penalty.

$$\log(wage)_i = \beta 0 + \beta 1(kids)_i + \beta 2(demographics)_i + \beta 3(exper)_i + \beta 4(hh)_i + \beta 5(educ)_i + u_i \tag{3}$$

The Mincerian wage model shown in (3) includes observed characteristics that are likely to affect wages. This regression has the advantage of allowing researchers to study the difference in wages for women by the number of children they have, holding all other observed characteristics constant (Wooldridge, 2015). This is a clearly advantageous model over (1).

The coefficients in the Mincerian wage regression will again be unbiased only if the zero conditional mean assumption holds or, in other words, if the unobserved characteristics in the error term are uncorrelated with the explanatory variables (Wooldridge, 2015). For this to be true, we must assume that there aren't any unknown characteristics that differentiate the sample of mothers from the sample of non-mothers.

However, many researchers worry that mothers do differ from non-mothers in unobserved ways, and this affects the wages that mothers and non-mothers receive (see Anderson et al., 2001; Budig and England, 2001; Wilde et al., 2010). For example, personal characteristics such as ambition, tenacity and productivity are likely to impact upon the wages a worker receives. These characteristics are almost impossible to measure, and so typically fall into the error term of a regression model. It may be true that women who are more ambitious or who are productive workers are also less likely to become mothers, or to have many children. If this is the case, then characteristics in the error term will affect the key independent variable (motherhood) in a linear regression model. This means that the zero conditional mean assumption will fail, and the OLS estimates will be biased (Wooldridge, 2015). This is known as unobserved heterogeneity (Wooldridge, 2015).

To control for unobserved heterogeneity, many researchers turn to panel data and fixed effects estimators. Panel data follows the same individuals over time, allowing researchers to track how wages changed for the same woman over time. The error term in panel data can be divided into two parts: the unobserved, time-invariant error term (a_i), which remains constant over time, and the unobserved time- varying error term (u_{it}), which changes for each individual over time.

$$y_{it} = \beta x_{it} + a_i + u_{it} \tag{4}$$

In equation (4), the dependent variable, y_{it} is a function of an explanatory variable and both the time- invariant and time-varying error terms. Researchers can use panel data to remove the unobserved, time- invariant error term (Wooldridge, 2015), controlling for any unobserved heterogeneity caused by a_i.

The most popular method to control for unobserved heterogeneity in the literature is to use a fixed effects estimator (for example, see Anderson et al., 2002; Kahn et al., 2012; Staff and Mortimer, 2012; Killewald and Gough, 2013; Grimshaw and Rubery, 2015). Fixed effects removes the time-invariant error term by averaging the fixed effects regression model (4) over time for each individual i. This is shown below in equation (5).

$$\bar{y}_i = \beta 1 \bar{x}_i + a_i + \bar{u}_i \tag{5}$$

Since ai remains constant over time for each individual, its value does not change. To remove a_i, we subtract (5) from (4), to get equation (6) below (Wooldridge, 2015).

$$\ddot{y}_{it} = \beta 0 + \beta 1 \ddot{x}_{it} + \ddot{u}_{it} \tag{6}$$

Thus, fixed effects controls for time-invariant characteristics of individuals, reducing unknown differences between the sample of mothers and non-mothers. Some researchers have found substantial differences in characteristics between mothers and non-mothers. Notably, Anderson et al (2002) found that their estimated motherhood penalty fell from 16% for women with one child using pooled OLS, to 4% per child using fixed effects (Anderson et al., 2002).

However, fixed effects can only control for unobserved heterogeneity caused by the time-invariant error term and cannot account for heterogeneity that changes over time (Hill et al., 2020). When using fixed effects, researchers also assume that preferences and attitudes remain constant over the period in which the data was collected. It is not clear that this is the case. On the contrary, women's preferences and beliefs about their career goals and ambitions may change in anticipation of having a child, or once they have had a child, as they work out how to balance their work and childcare commitments (Kahn et al., 2014).

Another panel data method that works to remove unobserved heterogeneity is the first difference estimator. Briefly, first difference works in a similar way to fixed effects, but instead of averaging individuals across all waves, it averages individuals between subsequent waves. If the characteristics that cause heterogeneity do not change over time, first difference successfully removes the time- invariant characteristics for individuals over waves (Wooldridge, 2015).

It is often difficult to know whether first difference or fixed effects is appropriate (Wooldridge, 2015), and so many researchers working with panel data present both results (for example, see Gough and Noonan, 2013). In this analysis, I will also present both fixed effects and first difference results.

Panel data methods, such as fixed effects can also make measurement error worse, as errors can be repeated and amplified over time. Measurement error occurs when the variable of interest is measured incorrectly (Wooldridge, 2015). This can happen when respondents do not understand a survey question correctly, or are incentivised to answer incorrectly, or if data is collected incorrectly (Wooldridge, 2015).

Measurement error is especially a problem when an explanatory variable is measured incorrectly, and the error in measurement is correlated with the observed value of the explanatory variable (Wooldridge, 2015). This is known as attenuation bias, and causes coefficients measured with error to be closer to zero than the real value of the variable (Wooldridge, 2015).

Measurement error in the earnings variable (the dependent variable) is of concern in many studies on the motherhood wage penalty (for example, see Jee et al., 2019 and Magadla et al., 2019). Survey respondents often answer questions on income incorrectly, either overstating, or understating their actual earnings. Measurement error of the key independent variable in the motherhood wage penalty research – motherhood, or the number of children a woman has given birth to – is less of a concern than in other applications.

Nevertheless, most studies agree that using fixed effects to control for some unobserved heterogeneity is an improvement on standard OLS analysis.

2.4.3.2. Spurious Correlation

The relationship between childbearing and wages is not clear, and researchers must contend with the fact that the relationship may be backwards: instead of childbearing affecting wages, women with lower wage potentials, or those who believe that their wages may decrease in the future, may be more likely to have more children (Avellar and Smock, 2003; Grimshaw and Rubery, 2015). To account for potential spurious correlation, panel data methods such as fixed effects and first difference can again be utilized, which allows researchers to study wages of women before and after having a child (or additional children).

2.4.3.3. Sample Selection Bias

Although fixed effects and first differencing can partially solve the problems of unobserved heterogeneity and spurious correlation, selection into employment may still introduce bias. Since we only observe the dependent variable for a subset of the sample, bias can be introduced into an OLS regression, as the sample is no longer random if women who work differ in some unobservable way from women who do not work (Wooldridge, 2015). Women who may be worst affected by a motherhood wage penalty, either due to low productivity, ambition, or wages, may be most likely to self-select out of employment (Avellar and Smock, 2003). Although this is a problem for all papers on the motherhood penalty, few researchers grapple with the problem and the impact on their results. Those that do attempt to solve selection into employment make use of imputation or Heckman models.

Some researchers have attempted to solve the selection problem by imputation. Since wage data is available only to women who are working, researchers assign imputed wage values for all women in the sample without wages. This allows researchers to use the full sample of women and to study the wage penalty as if all women in the sample were employed. For example, Kahn et al., (2014) assigned imputed values for wages and occupation status for women that did not work in their study of the motherhood wage penalty in the United States. The authors found that there was little difference in the extent of the penalty in between the original sample of working women, and the sample including women with imputed values (Kahn et al., 2014). However, this solution does not address any potential unobserved differences between women who work and those who do not.

Researchers have also used the Heckman model to correct for sample selection bias. The Heckman model is a two-stage estimation method. In the first stage, the probability of working is modelled for all women in the sample using a probit model. In the second stage, a transformed version of the probability of working is included as an explanatory variable in the original wage regression, controlling for any potential sample selection bias (Wooldridge, 2015). Although the Heckman model can, in some instances, solve the problem of selection into employment, it cannot provide explanations for why women choose to work, or not to work, in the first place. Moreover, it is also often unclear whether the Heckman model results, or the original regression results are better (Grimshaw and Rubery, 2015). Thus, I do not present Heckman results in my analysis below.

2.5. Contributions of this Dissertation

Although there has been much research on the motherhood wage penalty around the world, there is a lack of research of how motherhood – and children – affect women's earnings in developing countries. Moreover, the relationship between fertility and employment is not well understood in South Africa, a country with low employment opportunities, but similar fertility to other developing countries. Although there have been studies on both fertility and the motherhood wage penalty in South Africa using the NIDS dataset (for example, see Burger et al., 2012; Timaeus and Moulhie, 2015, and Mgadla et al., 2019), there have been few studies on the relationship between fertility, age and employment in South Africa. In this dissertation, I make two contributions to the literature: first, I provide an analysis of the motherhood wage penalty in South Africa using panel data, which is widely accepted to be a stronger method for measuring the motherhood wage penalty, and second, I explore the relationship between fertility and employment in South Africa.

3. Data Description

3.1. Data Description

In this dissertation, I use data obtained from the National Income Dynamics Study (NIDS) panel survey. NIDS is the first nationally representative household panel survey conducted in South Africa (Brophy et al., 2018). It followed individuals in South Africa between 2008 and 2017 over five waves. The survey includes information on fertility, labour force participation, economic activity, poverty, health and wellness, education, and human capital formation, among other variables, for individuals living in South Africa over time (Brophy et al., 2018). In 2008, 26 776 individuals were successfully interviewed in the first wave of NIDS. In this study, I restrict the sample of individuals to adult women – women aged 15 or older, according to the definition set in NIDS (Brophy et al., 2018). South Africa is one of the most unequal societies in the world, and inequalities are largely structured around race. To account for differences in inequalities by race, many researchers choose to only study one population group. For example, Mlatsheni and Leibbrandt, 2001 included only African individuals in their study on the relationship between fertility, education, and employment in South Africa (Mlatsheni and Leibbrandt, 2001). Following these researchers, I further restrict my sample to African women only, leaving a sample size of 7 328 women.

3.2. CSMs and TSMs

As a panel survey, the NIDS team surveyed the same individuals over five waves. These individuals are known as Continuing Sample Members (CSMs). Any other individuals present in the CSMs' household during the interview were interviewed too. These individuals, known as Temporary Sample Members (TSMs), are included in the data but are not tracked by NIDS over time (Brophy et al., 2018). Table A1 in the Appendix shows the number of CSMs and TSMs present in all five waves of data, first for all individuals, and then for African women only. Although TSMs could be included in the data over multiple waves (ie: if they resided with a CSM over multiple waves), when using the dataset as a panel, I include only the CSM individuals. The reason for this is twofold: firstly, NIDS did not include panel weights for TSM individuals. Following this, I excluded TSM individuals from the panel weights I created for this analysis (this is explained in further detail in the next section). Secondly, including only CSM individuals ensures that the sample is nationally representative.

However, when I look at only one wave of data, or analyse the pooled dataset, I include both the CSMs and TSMs, to include a larger sample size. This is potentially problematic if the sample of TSMs differs substantially from the sample of CSMs, as it will mean that the pooled data analysis results cannot be compared to the panel data analysis results. To check this, whenever I include TSMs in a table, figure, or regression, I repeat the process using only CSM individuals. This is consistent with the work done by Garlick et al (2016), who analysed samples of both CSM and TSMs for Wave 1 in their study (Garlick et al., 2016). These results, for CSMs only, can be found in the appendix. None of the results differed substantially when including only CSM individuals.

3.3. Weights

One reality of using panel data is correcting for non-random attrition between waves of data. If individuals who were initially surveyed refuse to participate in additional surveys, and this refusal is correlated with some characteristic (such as wealth, or race), the refusal or "attrition" will create bias in the survey results. NIDS corrects for this attrition by using inverse probability weighting, where individuals who were present in subsequent waves are weighted by the inverse of the probability of being present in the subsequent wave, given their wave 1 characteristics (Branson and Wittenberg, 2019). These weights were created only for CSMs.

Moreover, NIDS only created weights for CSMs between wave 1 and the subsequent wave[5] (Branson and Wittenberg, 2019). Since I use the panel dataset to study changes over time starting in waves other than wave 1, I created my own weights for this analysis. Following the NIDS team, I used inverse probability weighting to create weights for each wave both one and two wave ahead. First, I ran a Probit model to estimate the probability that an individual who was present in wave 1 would be present in subsequent waves. This is shown in equation (7) below, where $\Pr(attrition)$ refers to the probability of a respondent not being present in a subsequent wave, $\beta 0$ refers to the constant, β_i characteristics of the respondent, and μ_i refers to the error term in the regression.

$$\Pr(attrition) = \beta 0 + \beta_i + \mu_i \tag{7}$$

Following Brophy et al. (2018), I included the following characteristics of the respondent in the probit model: age of respondent, education level, race, gender, province, household size, whether the respondent lives alone or not, missing household income, geography, questionnaire type, respondent's intention to relocate, respondent's attitude, and respondent's attention during the data collection process.

After running the probit regression, I predicted the probability that an individual would attrit, and then created the inverse probability weights for individuals who were present in subsequent waves by dividing the cross-section weights by the inverse of the probability an individual with similar characteristics would attrit. This is shown in equation (8) below.

$$IPW_i = crossweight_i/(1 - attrithat) \tag{8}$$

Where IPW_i refers to the inverse probability weight created for individuals present in subsequent waves, $crossweight_i$ refers to the cross-section weight assigned to each individual and $(1 - attrithat)$ refers to the inverse probability that an individual would attrit.

Finally, I trimmed the top and bottom 1% of each weight I created, following Branson and Wittenberg (2019). To ensure consistency between the weights I created, and the original NIDS weights, I provide key statistics for both the NIDS weights and the inverse probability weights I created in the appendix, under Table A2.

[5] NIDS created weights between W1-W2, W1-W3, W1-W4 and W1-W5 (Branson and Wittenberg, 2019).

4. Fertility, Age and Labour Market Outcomes

Women's fertility is closely linked to their labour market outcomes, as well as their age. Researchers have found a negative relationship between labour market participation and fertility: women who are employed, or participating in the labour market, have fewer children than women who do not participate in the labour market (Fang et al., 2013). Women's fertility is also limited by their age. In this section, I look at the links between fertility, age and labour market outcomes for African women in South Africa.

4.1. Labour Market Outcomes

In the first quarter of 2021, South Africa had a strict unemployment rate of 32.6% (Statistics South Africa, 2021), one of the highest unemployment rates in the world. Female unemployment was slightly higher – 34.6% of women in South Africa were unemployed in the first quarter of 2021, while just over half of women participated in the labour force (Statistics South Africa, 2021). South Africa has grappled with extremely high unemployment rates for decades (Lam et al., 2008). Youth unemployment is particularly a problem in South Africa – young people in South Africa are consistently less likely to find work than older cohorts, and young women are more likely to be unemployed than young men (Ingle and Mlatsheni, 2017). Previous research has shown that African women have the lowest labour force participation rate and employment rate of all race groups (Casale, 2004). Studying the labour market outcomes of African women is important as this will lay the foundation for understanding the motherhood penalty, and which women are included or excluded from the analysis.

To study the labour market outcomes of African women in South Africa, Table 1 below presents labour market outcomes for African women in Wave 1 of NIDS[6]. Older cohorts of women (up until the age of 49) are more likely to be employed than younger cohorts: around 50% of women aged between 35 and 49 are employed, compared with only 20% of women aged between 20-24. Strict unemployment is highest for women aged 25-29. This is reduced in older cohorts as women either become employed or leave the labour market. From age 50 onwards, the percentage of women not involved in the labour market increases substantially.

Table 1: Labour market status by age category for African women in Wave 1 (%)

	African Women									
	15-19	**20-24**	**25-29**	**30-34**	**35-39**	**40-44**	**45-49**	**50-64**	**65+**	**Total**
NEA	85,14	35,96	22,26	23,45	19,69	21,48	30,55	55,95	86,52	44,04
Discouraged Worked	3,42	12,62	8,53	8,80	10,75	6,68	4,93	2,61	0,09	6,73
Strict Unemployed	6,84	29,95	31,96	26,01	19,05	19,33	13,72	4,53	0,03	17,35
Employed	4,60	21,47	37,24	41,74	50,51	52,51	50,81	36,91	13,35	31,88
Total	100	100	100	100	100	100	100	100	100	100
N	**1 182**	**1 057**	**915**	**802**	**705**	**586**	**500**	**1 013**	**506**	**7 266**

Data Source: NIDS Wave 1. Data is weighted using Wave 1 cross-section weights. Weighting accounts for complex survey design. Columns sum to 100. Broad unemployment includes strictly unemployed and discouraged workers. "NEA" refers to Not Economically Active.

[6] Since I use NIDS as a weighted dataset, the difference in labour market status by age category for African women in different waves of NIDS is negligible. I decided that it was not necessary to conduct additional analysis on labour market status for women in other waves of NIDS.

The South African labour market is characterised by low employment rates, especially for African women (Ingle and Mlatsheni, 2017). Overall, 32% of African women in South Africa were employed in 2008, while 44% were not participating in the labour force.

To study whether the employment and labour force participation rates experienced by African women in South Africa is 'normal', I now compare the labour force participation ratees and employment rates in South Africa to that of women in other countries. This is shown below in Table 2.

It is clear from the table that South African women have much lower employment rates than women in other countries. In developed countries such as the United States and the United Kingdom, for example, the employment rate for women stood at 54% and 52%, respectively (International Labour Organization (ILO), 2008). Other developing countries also had higher employment-to-population ratios than South Africa: in Russia, 58% of women were employed in 2010, and in Brazil, 47% of women were employed in 2012 (ILO, 2020). This is significantly higher than South Africa's employment rate of 32% for African women in 2008. This is also consistent with the findings of other researchers. For example, Magruder (2012) found that only 39,66% of South African women were employed in 2003, compared with 49,70% of Brazilian women in 1995. The consistently low employment rate for women is of interest, as this may affect fertility in South Africa. Previous research has shown that as economic opportunities increase for women, fertility rates fall (Krafft, 2020). It is thus interesting to study fertility in a country with such low employment rates for women, and young women in particular.

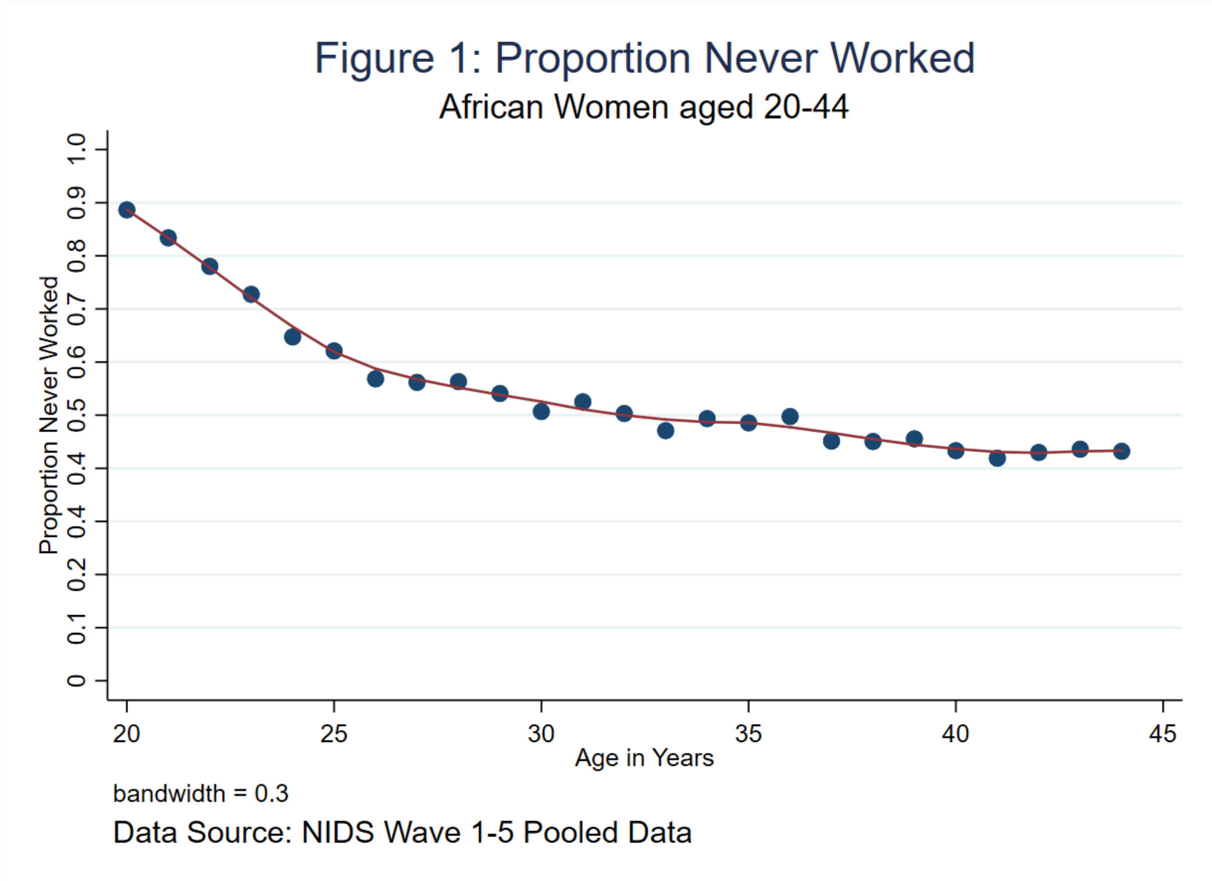
Table 2: Cross-Country comparison of Employment and Labour Force Participation Rates

Country	Year of survey	LFPR (%)	% Employed
African women in South Africa	2008	52,90	33,26
All South African women	2008	53,33	36,66
United States	2010	57,50	53,60
United Kingdom	2010	55,50	52,20
Canada	2010	61,90	57,90
Russia	2010	55,90	58,00
Argentina	2010	48,00	43,60
Brazil	2012	53,00	47,00
Bolivia	2012	57,90	56,50

Data Sources: NIDS Wave 1 (South Africa). International Labour Organization, n.d. (all other countries). NIDS data is weighted using Wave 1 cross-section weights, and accounts for complex survey design. NIDS sample includes women aged 15-65. LFPR stands for labour force participation rate. All other countries include women of all race groups.

Table 2 also shows that South African women cannot find work, despite having similar labour force participation rates to other developing countries. For example, 53% of Brazilian women are in the labour force, and 47% are employed. In contrast, although 53% of South African women also participate in the labour force, only 37% are employed.

Table 2 also shows that, similar to other developing countries, South African women have a lower labour force participation rate compared with developed countries. This low labour force participation rate for women in South Africa can also be shown by looking at the proportion of women in NIDS who reported to have never worked. To do so, Figure 2 shows a Lowess Curve of the proportion of African women aged between 20 and 44 who have never worked, pooled across all five waves of NIDS. Lowess curves derive their value at a single point by estimating the value of any points "near" it. The bandwidth of the lowess function (here, set at 0.3) determines which points are included in the estimation at any point in the curve, with points receiving more weight if they are closer to the centre of the estimation (Wittenberg, 2001). The Lowess curve includes all women in the pooled dataset – including Temporary Sample Members (TSMs). Since I will be excluding TSMs in the regression analysis, I redo the Lowess Curve only for Continuing Sample Members (CSMs). The results do not change substantially – in both Lowess Curves, young women are substantially less likely to work than older women. The Lowess Curve including only CSMs can be found in the Appendix, labelled Figure A3.



Consistent with the literature, the graph shows that a very high proportion of young women have never worked, and this decreases as women age. Importantly, close to half of African women in their 30s report to have never worked – and this decreases only slightly for women in their 40s. Nevertheless, close to 40% of women in their 40s and 50s have never worked. Previous researchers have also found that a high proportion of individuals in South Africa (and women in particular) have never worked. Kingdon and Knight (2004), for example, found that 83% of South Africans aged between 16-24 who were unemployed had never worked before, and close to 50% of 46–55-year-olds had never worked (Kingdon and Knight, 2004). For women, a higher proportion had never worked than men: the authors found that 70% of unemployed women had never worked, compared with 59% of unemployed men (Kingdon and Knight, 2004).

Having a high proportion of women who have never worked may present a problem for studying the motherhood wage penalty, as these women would necessarily be excluded from the analysis. I discuss this in more detail in Section 4.3 below. The Lowess curve, however, tells only part of the story, as some young women may have never worked because they are either still at school or studying in a tertiary institution.

This distinction between young women who have never worked because they are in education and training and those who have never worked because they cannot find work, or are discouraged workers, is an important one in the South African context. There is a high demand for skilled workers in the South African economy, and a surplus of medium and low-skilled workers (Bhorat and Kahn, 2018). Given this bias for skilled workers in South Africa, young people who are not in the labour force because they are in education or training are likely to have a higher chance of employment when they do enter the labour force. These types of workers can be distinguished using the NEET Indicator[7] – one of the International Labour Organization's indicators for decent work in an economy (ILO, 2018). The NEET Indicator specifies the share of young people (aged between 15-24) who are not employed, in education or training (ILO, 2018). This indicator allows a distinction between young people who are not employed because they are pursuing education, and those who are not employed because they cannot find work or have left the labour force. In this way, it provides a snapshot of the potential labour supply of young people in an economy (ILO, 2018). For example, a 20-year-old woman who is not working or pursuing tertiary education or training in South Africa, will be less employable in the future than a 20-year-old woman who is currently in tertiary education, or who is already employed.

Table 3 below presents the percentage of young women in countries around the world who were NEET between 2008 and 2010. It is clear from the table that a much larger proportion of South African women (both when looking only at African women, and when looking at all South African women) are NEET compared to other young women around the world. In developed countries such as Canada, only 14% of young women are NEET. The percentages are higher in developing countries – in Argentina and Brazil, for example, 24% and 26% of young women were NEET in 2010, respectively. However, this is substantially fewer women than in South Africa – close to 40% of young African women in South Africa were NEET in 2008. This is important because policymakers warn that NEET status can negatively affect young people's economic prospects well into the future (ILO, 2018). Young women who are NEET may be less likely to receive a high paying job, or even be employed in the future.

Table 3: Cross-Country Comparison of female NEET Youth

Country	Year	% NEET

[7] The NEET indicator is calculated by dividing the number of young people not employed or in education/training by the total number of young people in a country.

African women in South Africa	2008	38,04
All South African women	2008	37,36
United States	2010	20,20
United Kingdom	2010	15,20
Canada	2010	13,50
Russia	2010	18,20
Argentina	2010	24,30
Brazil	2010	25,80
Bolivia	2010	16,50

Data Sources: NIDS Wave 1, 2008 (South Africa). International Labour Organization, n.d. (all other countries). NIDS data is weighted using Wave 1 cross-section weights, and accounts for complex survey design.

To study the relationship between NEET status and employment status, I leverage panel data. Table 5 below presents the NEET status for African women aged 20-24 and tracks their labour market outcomes two and four years later.

Table 4: Labour market outcomes for African women by NEET status

			Employment Status (T+1)		
		NEA	**Broad Unemployment**	**Employed**	**Total**
	NEET=0	33,23	26,60	40,17	100
NEET Status	**NEET=1**	36,63	37,84	25,53	100
	Total	35,18	33,04	31,78	100
	N	645	606	583	1 834
			Employment Status (T+2)		
		NEA	**Broad Unemployment**	**Employed**	**Total**
	NEET=0	27,96	20,72	51,33	100
NEET Status	**NEET=1**	36,15	27,69	36,16	100
	Total	33,00	25,01	41,99	100
	N	246	186	313	745

Data Source: NIDS Waves 1-5 Panel data. Data is weighted using panel weights to account for complex survey design and attrition. Broad unemployment includes strictly unemployed and discouraged workers. "NEA" refers to Not Economically Active. (T+1) refers to data collected one wave after the initial wave. (T+2) refers to data collected two waves after the initial wave.

Table 4 shows that women who were classified as NEET have lower employment rates both two and four years later. For example, only 26% of women who were classified as NEET in their early 20s were employed two years later. However, 40% of women who were not NEET in their early 20s were employed two years later. This increases to 51% of women employed four years later. Young women in South Africa struggle to find work, and Table 4 shows that, consistent with previous research, young people who invest in their human capital (either through employment or education) are more likely to be employed than young people who do not. This is significant for studying the relationship between economic opportunity and fertility – do women with lower economic opportunities (ie: women who were classified as NEET) have more children than women with greater economic opportunities?

Previous research has shown that there is a negative relationship between fertility and economic opportunity: as economic opportunities and employment prospects increase for women, so fertility decreases (Fang et al., 2013). Understanding fertility in South Africa – and how it affects women's labour force participation and employment prospects – is critical to understanding the motherhood wage penalty. Research on the motherhood wage penalty includes only women (both mothers and non- mothers) who are earning a wage – in other words, are employed. Given South Africa's high levels of unemployment, especially for young women, studying the motherhood penalty accurately in South Africa may be difficult. To further investigate this issue, in the next section I look at fertility in South Africa.

4.2. Fertility in South Africa

The Total Fertility Rate of a country is measured as the number of births per 1000 women of reproductive age – in other words, the average number of children a woman could be expected to have if she lived in a country for all her reproductive years, between the ages of 15 and 49. Before I study fertility decisions in South Africa, I present Table 5 below which provides an overview of both the Age- Specific Fertility Rate (the fertility rate by age category) and the Total Fertility Rate, which can be calculated from the Age-Specific Fertility Rate. Table 5 shows that the fertility rate found in NIDS is similar to that found by Statistics South Africa in 2008: in NIDS I estimate that the average woman in South Africa would have 2.48 children in her lifetime. Statistics South Africa estimates the fertility rate to be 2.61 children per woman in 2008 (Statistics South Africa, 2008). This is important because if the sample of women in NIDS had significantly more or fewer children than the national average found by Statistics South Africa, any analysis on fertility using NIDS would be incorrect.

Table 5: Age-Specific Fertility Rate (ASFR) of women in Wave 1 of NIDS

(1)	(2)	(3)	(4)
Age category	**Number of observations**	**Number of births**	**ASFR**
15-19	1 556	83	53,34
20-24	1 442	186	128,99
25-29	1 046	129	123,33
30-34	919	93	101,20
35-39	915	66	72,13
40-44	846	11	13,00
45-49	819	4	4,88
Total	**7 534**	**721**	**496,87**

Data Source: NIDS Wave 1, 2008. Own calculations for ASFR. "Number of births" refers to the number of births in a year – in this case, between July 2007 and July 2008. The ASFR is calculated by dividing (3) by (2) and multiplying by 1000. This provides the number of births per 1000 women in a specific age category. The total fertility rate (TFR) can be calculated by summing the ASFR, multiplying the total by 5 (to account for the five years that women spend in each age category) and dividing by 1000. This gives a TFR of 2.48 births per woman in South Africa between February 2007 and February 2008. This is similar to the Statistics South Africa's TFR estimate of 2.61 births per woman in South Africa in 2008 (Statistics South Africa, 2008).

South Africa's Total Fertility Rate (TFR) is comparable to other developing countries in Latin America. Table 6 below shows that South Africa has significantly lower total fertility than other African countries, such as Nigeria (5.9 children per woman in 2008) and Mozambique (5.52 children per woman). High income countries such as the United States, Canada and Japan have lower total fertility than that of South Africa – in 2008, all three high income countries had fertility rates below the replacement rate of 2.1 (World Bank, 2008).

Table 6: Cross-Country Comparison of Total Fertility Rate

Country	Year	Total Fertility Rate
South Africa	2008	2.48
Nigeria	2008	5.90
Mozambique	2008	5.52
United States	2008	2.07
Canada	2008	1.68
Japan	2008	1.37
Colombia	2008	2.08
Argentina	2008	2.37
Peru	2008	2.63

Data Sources: NIDS Wave 1, 2008 (South Africa). NIDS data is weighted using calibrated cross-section weights and accounts for complex survey design. World Bank, 2008 (other countries). Own calculations for South Africa's Total Fertility Rate (TFR).

Aside from confirming that the NIDS dataset can be used to study fertility, the ASFR and TFR is of limited use for this study. To understand how fertility affects earnings, it is much more important to understand the choices women make around their fertility – when they choose to have children, and why. To this end, Table 7 below shows when women first report giving birth, by age category. A total of 7 194 African women were aged between 15 and 64 in Wave 1. 687 women were excluded for not having information on whether they had given birth before, leaving a sample size of 6 507.

From the age of 20, most women in each age category have given birth. This is especially important for young women because, as shown in the previous section, young women are less likely to be employed than older women in South Africa. For example, Table 7 shows that 62% of women aged between 20-24 have given birth in Wave 1. However, as shown in Table 1 in the previous section, only 20% of 20–24-year-old women were employed. Understanding how employment – or lack thereof – affects women's fertility decisions is important and is discussed further below.

Table 7: Proportion of African women who have given birth by age category in Wave 1 (%)

	Age Category								
	15-19	20-24	25-29	30-34	35-39	40-44	45-49	50-64	Total
Yes	16,19	61,55	84,62	91,47	95,99	98,36	97,96	97,05	75,07
No	83,81	38,45	15,38	8,53	4,01	1,64	2,04	2,95	24,93
Total	100	100	100	100	100	100	100	100	100
N	1 139	1 016	889	766	681	564	478	974	6 507

Data Source: NIDS Wave 1. Data is weighted using Wave 1 cross-section weights. Row answer to the question "Ever given birth?"

Table 7 also shows that 16% of adolescents (15–19-year-olds) had given birth by 2008. Compared to other African countries, South Africa has a low adolescent fertility rate (World Bank, 2019), and South Africa's fertility and adolescent fertility rates have been declining (World Bank, 2019). In 2019, the adolescent fertility rate in South Africa was estimated to be 68 per 1000 births of women aged between 15-19. In contrast, Nigeria, Zimbabwe, and Mozambique had adolescent fertility rates of 104, 80 and 144 per 1000 births, respectively (World Bank, 2019).

Sub-Saharan Africa has the highest rate of adolescent fertility in the world (Novignon et al., 2019), and compared to countries outside of Africa, South Africa's adolescent fertility rate remains relatively high. In the United States, for example, the adolescent fertility rate in 2019 was 17 births per 1000 women (World Bank, 2019). Other developed economies such as Canada (7 births per 1000 women) and Japan (3 births per 1000 women) had even lower adolescent fertility rates (World Bank, 2019). South Africa's adolescent fertility rate is most similar to other developing countries in Latin America – in 2019, the adolescent fertility rates of Bolivia, Colombia and Argentina stood at 63, 64 and 62 births per 1000 women (World Bank, 2019).

The age at which women first give birth can often act as an indicator for their future educational and economic outcomes (Ranchhod et al., 2011; Garenne et al., 2001). In South Africa, the mean age women first give birth is 21.8 (Statistics South Africa, 2011). This is significantly lower than developed countries around the world, as shown by Table 8 below. Table 8 shows that women in developed countries, on average, first give birth more than five years later than women in Sou th Africa. In the United States, for example, the mean age at first birth is 25.6, while the mean age for women in Canada is 28.5 and 30.1 for women in Japan.

However, South Africa's mean age at first birth is similar to that of other developing countries. Women in other developing countries tend to give birth at a younger age than their counterparts in developed countries: the average age at first birth for women in Turkey, Cambodia, and Indonesia, for example, is 22.3, 22.4 and 22.0 respectively.

Table 8: Cross-Country Comparison of Age at First Birth

Country	Year	Mean age at first birth
South Africa	2011	21.8
Canada	2011	28.5
United States	2011	25.6
United Kingdom	2013	28.3
Japan	2011	30.1
Russia	2011	24.9
Turkey	2010	22.3
India	2006	19.8
Nepal	2011	20.2
Cambodia	2014	22.4
Indonesia	2012	22.0
Philippines	2013	23.5

Data Sources: Statistics South Africa, 2011 (South Africa). OECD, 2011 (Canada, United States, United Kingdom, Japan). United Nations, n.d. (Russia, Turkey). DHS, 2016 (India, Nepal, Cambodia, Indonesia, Philippines).

The age at which women first give birth is relevant because the earlier women give birth, the more children they are likely to have (Tomkinson, 2019). Women who give birth at a young age have a longer reproductive period than women who give birth at an older age, meaning they can give birth to more children (Tomkinson, 2019). Previous research has pointed to the negative relationship between fertility and economic prospects, although the direction of causality is unclear (Bernhardt, 1993). Women who are less inclined to participate in the labour market may choose to have more children. Alternatively, the action of having a child may affect women's labour force and employment decisions (Bernhardt, 1993).

In Sections 4.1 and 4.2, I explored labour market outcomes and fertility decisions for South African women, comparing these outcomes to women in other countries. Despite South African women having significantly lower employment rates than women in other countries – both developed and developing countries – as shown by Table 2, South Africa's Total Fertility Rate, age at first birth and adolescent fertility rate are similar to that of other developing countries – and lower than many African countries. This presents an interesting observation of the relationship between labour market outcomes and fertility: despite lower employment and higher NEET levels, South African women's fertility decisions remain relatively similar to women in countries with similar levels of development, although these countries all have higher employment rates. The relationship between labour market outcomes and fertility is complicated, and a descriptive analysis cannot tackle questions of causality. However, the relationship between fertility and employment is also important for studying the motherhood wage penalty – given that most women in South Africa are not employed, and most women give birth at a relatively young age, often before finding work, challenges with measuring the motherhood wage penalty may arise. In the next section, I look at how South Africa's fertility and economic outcomes will affect studying the motherhood wage penalty.

4.3. How fertility and employment will affect the Motherhood Wage Penalty

In the previous sections, I have shown that most women in South Africa have given birth, and that most women are not employed. Both present challenges for studying the motherhood wage penalty using Ordinary Least Squares (OLS) and panel data methods. For panel data methods, for example, studying a wage penalty necessitates including only individuals that are earning a wage in more than one period. Excluding individuals who are not employed may create a sample selection problem for both OLS and panel data methods. Furthermore, to compare the wages of women with children and women without children, I need a sample of non-mothers and, essential to panel data, changes in the number of children women have over time. To check that there are changes in childbearing over time, Table 9 presents changes in the number of children, aged 18 and younger, employed women have given birth to over one and two waves.

Table 9 shows that there is movement in the number of children women have over time. 19% of women who did not have children initially, had one child one wave later. Two waves later, this increases to 33% of women with one child. For women who already had children, there is also movement over time. 16% of women who had one child initially had two children two years later, while 11% of women who had two children initially had three children two years later. Consistent with the literature, the number of women who have more than three children is low, which accounts for the low movement into the 4+ category. Roughly 15% of women have four or more children.

Table 9: Percentage changes in the number of children for employed women

		Number of Children (T+1)					
		0	**1**	**2**	**3**	**4+**	**T**
Number of Children (T)	**0**	80,94	18,72	0,34	0	0	**100**
	1	0	82,76	16,50	0,74	0	**100**
	2	0	0	89,44	10,50	0,06	**100**
	3	0	0	0	90,90	9,10	**100**
	4+	0	0	0	0	100	**100**
	T	**10,65**	**23,63**	**29,64**	**21,13**	**14,94**	**100**
	N	**245**	**543**	**681**	**485**	**343**	**2 297**
		Number of Children (T+2)					
		0	**1**	**2**	**3**	**4+**	**T**
Number of Children (T)	**0**	62,67	33,83	3,50	0	0	**100**
	1	0	57,16	39,87	2,81	0,16	**100**
	2	0	0	81,88	17,12	1,00	**100**
	3	0	0	0	86,41	13,59	**100**
	4+	0	0	0	0	100	**100**
	T	**8,33**	**19,59**	**33,49**	**24,13**	**14,46**	**100**
	N	**60**	**140**	**240**	**173**	**103**	**716**

Data Source: NIDS Wave 1-5 Panel. Data is weighted using panel weights to account for complex sample design and attrition. (T+1) refers to data collected one wave after the initial wave (T). (T+2) refers to data collected two waves after the initial wave. Sample includes employed African women aged between 20-44.

The relationship between having a child and working is also complicated – if women stop working after having a child, they will be excluded from the analysis, and not captured in a motherhood wage penalty analysis, although this is another penalty of sorts – a motherhood employment penalty. Some researchers have tackled this question of a motherhood employment penalty, tracking how labour market outcomes as well as wages change for women as they become mothers (Khan et al., 2014). In this dissertation, however, I will only be looking at a wage penalty.

Another issue is how the sample of employed non-mothers and mothers differ. If most non-mothers are young women, and young women in South Africa are less likely to find work, the sample of non - mothers will be substantially smaller than the sample of mothers. This could make an analysis comparing mothers to non-mothers challenging. Indeed, this is what I found in the previous sections – Table 7 in the fertility section showed that most women (83%) have given birth before the age of 30. Table 1 in the Labour Market section showed that employment rates increase as women age, with the highest percentages of employed women aged between 35 and 44.

To investigate this further, Table 10 below presents the percentage of employed mothers and non - mothers by age category. The table seems to suggest two forces at play: younger women who do not have children are more likely to be employed. However, as women age (and more women move from the non-mother to mother category), employment increases for mothers and decreases for non-mothers. As most of the sample transition from non-mother to mother as women age, the increase in employment for mothers may reflect the increase in employment prospects for women as they age. Since Table 10 again includes both CSM and TSM women, I include the same summary statistics for CSM mothers and non-mothers in Appendix A4. The results do not change substantially when TSM women are excluded.

Table 10: Percentage of Employed Mothers and Non-Mothers by age category

	Mother	**Non-Mother**	**Total**
20-24	8,66	37,51	12,79
25-29	22,27	31,97	23,66
30-34	26,48	16,79	25,10
35-39	23,36	9,59	21,39
40-44	19,23	4,13	17,07
Total	**100**	**100**	**100**
N	**7 503**	**1 008**	**8 511**

Data Source: NIDS Waves 1-5 pooled data. Data is weighted using calibrated cross-section weights and accounts for complex survey design.

Table 10 shows that the sample of female earners will largely be made up of mothers, which will affect my analysis, as regression analysis also requires a sample of non-mothers who are employed. If the sample of employed non-mothers is too low, it will be impossible to compare the wages of women as they transition to becoming mothers. Moreover, having a small sample size may reduce the significance of regression results (Wooldridge, 2015). Table 11 below presents a transition matrix for employed women only, showing how women move from non-mothers to mothers in NIDS. Most women are mothers: initially, only 13% of the sample is not a mother. One wave later, only 11% of women were non-mothers and two waves later, only 9% of women were non-mothers. In other studies, the majority of women are mothers too, although there is typically a higher percentage of non-mothers. Aguero et al., (2020) pooled data from 22 low-and-middle income countries to study the motherhood wage penalty across countries. 22% of their sample were non-mothers (Aguero et al., 2020). Other researchers in the United States found that 40% of their sample of women were not mothers at age 25. However, this reduced to 14% of the sample not being mothers by age 45 (Khan et al., 2014).

Table 11: Transition Matrix of Motherhood Status for Employed Women

		(T+1)			(T+2)		
		10,95	89,05	100	9,72	90,28	100
		Non-Mother	**Mother**	**T**	**Non-Mother**	**Mother**	**T**
13,25	**Non-Mother**	80,94	19,06	100	62,67	37,33	100
86,75	**Mother**	0	100	100	0	100	100
100	**T**	10,86	89,14	100	8,85	91,15	100
	N	**244**	**2 001**	**2 245**	**93**	**1 074**	**1 167**

Data Source: NIDS Wave 1-5 Panel. Data is weighted using panel weights to account for complex sample design and attrition. Each wave is two years apart. (T+1) refers to data collected two years after the initial wave. (T+2) refers to data collected four years after the initial wave.

The transition matrices above include a specific subset of women – women who are employed in two waves. Having a sample of women employed in two or more waves is necessary for studying the motherhood penalty using fixed effects. Leveraging NIDS as a panel dataset again, I can provide a more nuanced view of labour market changes for women over time. Table 12 presents labour market outcomes in Wave 1 and two years later in Wave 2 for African women aged between 20-44 in Wave 1. In Wave 1, a total of 38% of women were employed, which remained roughly constant in Wave 2. Of that sample of employed women in Wave 1, however, 73% remained employed in Wave 2. This means that, in a fixed effects regression analysis, 70% of the employed sample of women in Wave 1 (already a minority of women) would be eligible for analysis.

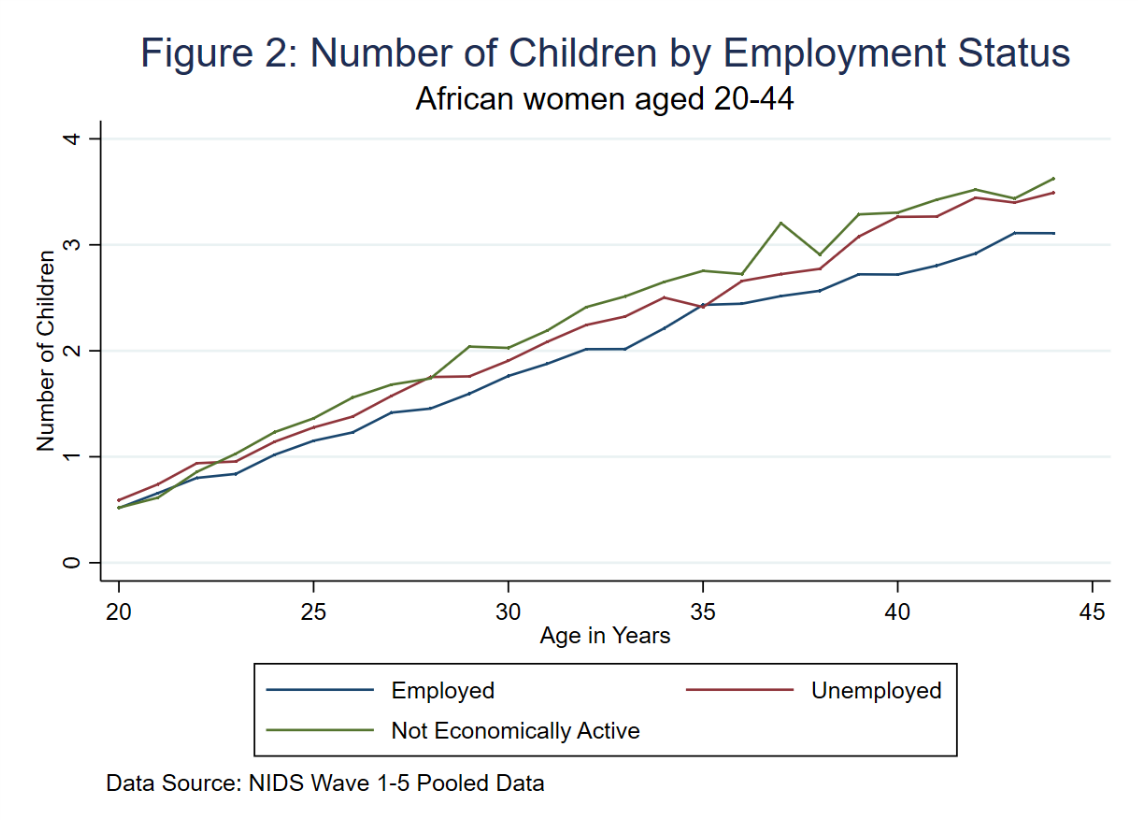
Table 12: Transition Matrix of Employment Status for African women in Wave 1

			Wave 2				
			40,07	6,30	18,86	34,77	100
			NEA	**Discouraged**	**Strict**	**Employed**	**Total**
	25,50	**NEA**	40,67	6,63	28,06	24,64	100
Wave 1	9,76	**Discouraged**	42,69	3,71	28,42	25,18	100
	26,20	**Strict**	31,60	6,04	35,58	26,79	100
	38,53	**Employed**	12,18	1,32	13,22	73,27	100

100	**Total**	28,72	4,41	24,03	42,84	100
	N	**833**	**128**	**698**	**1 243**	**2 902**

Data Source: NIDS Wave 1 and 2. Data is weighted using Wave 2 panel weights to account for complex survey design and attrition. Table presents labour market outcomes for women age between 20 -44 in Wave 1. "Discouraged" refers discouraged workers. "Strict" refers to strict unemployment. "NEA" refers to Not Economically Active.

Given that most women in South Africa are mothers, it is possibly more interesting to study the extent to which additional children are correlated with women's labour market outcomes. Figure 2 below shows the average number of children by employment status for African women of childbearing age (between the ages of 15-49) using NIDS Waves 1-5 as a pooled dataset. Consistent with the literature, Figure 2 shows that women who are employed have fewer children, while women who are not in the labour force have the most children. Since Figure 2 includes both CSM and TSM women, I recreate Figure 2 in Appendix A5 using only CSM women. The trend between employment status and number of children remains the same.



However, although Figure 2 shows that, on average, employed women give birth to fewer children, it does not show how changes in the number of children women give birth to affects employment. Table 13 leverages panel data to show the changes in the percentage of women employed as they give birth to more children.

Table 13: Percentage of Women Employed by Changes in Number of Children

	Percentage Employed	Percentage Employed (T+1)	Percentage Point Change in Employment
0-0	36,96	47,31	10,35
0-1	31,44	32,63	1,19
1-2	34,70	36,46	1,76
2-3	39,72	39,51	-0,21
3-4+	39,80	36,89	-2,91

Data Source: NIDS Wave 1-5 Panel data. Data is weighted using panel weights to account for complex survey design and attrition. Table includes women aged between 20-44. (T+1) refers to data collected two years after the initial wave.

Table 13 shows that having additional children is correlated with changes in the employment probabilities of women. Women who did not have any children in either wave saw an increase in employment of 10.35 percentage points. For women who went from not having children, to having one child, there was a 1.19-percentage point increase in employment probability. However, women who went from having two to three children, or three to four or more children, saw declines in employment probabilities between waves. This is an important part of studying the motherhood wage penalty – while being a mother may affect wages, the number of children women give birth to will also be important. Women who have more children may be affected more by "motherhood" than women with fewer children.

In Section 4, I have shown that the relationship between fertility, age and labour market outcomes is complicated in South Africa. South African women face low economic opportunities – a high proportion of women have never worked or are unable to find work. However, despite women facing low economic opportunities, fertility levels in South Africa are similar to those in other developing countries, with better economic opportunities for women. This presents additional challenges to studying the motherhood wage penalty in South Africa, as most women are not employed. This means that a large proportion of the sample will be excluded from the analysis. Moreover, if most women are mothers, then comparing the earnings of mothers and non-mothers will be difficult. To remedy this, as well as looking at the effects of children on women's earnings, I also look at how the number and age of children affect mother's earnings in the next section.

5. The Motherhood Wage Penalty

5.1. Descriptive Analysis

As shown in the previous section, comparing the wages of mothers and non-mothers in South Africa is complicated. Most women have children, and many have children even before they begin working. There is also a positive correlation between earnings and age in South Africa, with individuals becoming more likely to earn more as they age.

For the rest of the dissertation, I restrict my sample to African women aged between 20-44, to control for school-leavers entering the labour force, and older women leaving the labour force. I also restrict my sample to women who are employed. This is no small matter in South Africa, a country with one of the highest unemployment rates in the world. In the pooled dataset, this means removing 64% of the sample of African women who report being unemployed or not economically active – reducing the pooled sample from 25 099 women to 9 121 women[8]. A further 311 women aged between 20-44 who did not report whether they have given birth or not were also excluded.

In most research papers looking at the motherhood wage penalty, the dependent variable is usually hourly or weekly wages, or monthly earnings. However, in the NIDS questionnaire, the question on monthly earnings for individuals' main job[9] was asked only to those individuals who reported earning a salary or wage on a regular basis. This excludes any workers employed in casual or self-employment. Previous research has shown that casual and self-employment are mostly transitory types of employment, with most South Africans preferring regular employment (Cichello et al., 2014). Nevertheless, excluding earnings from casual and self-employment may affect the analysis in important ways.

Thus, the dependent variable used in this analysis is monthly take-home pay. This includes take home pay for both primary and secondary occupations, regardless of whether those occupations are classified as regular, casual or self-employment. Monthly take-home pay also includes imputed values for individuals who refused to answer (Brophy et al., 2018). The variable has been deflated using Statistics South Africa's consumer price indices and are deflated to December 2016. As a quality check, the top and bottom 1% of earners are excluded from the analysis, as well as any individuals who reported earning zero income.

The key independent variable is the number of children a woman is reported to have given birth to. Following the literature (for example, see Grimshaw and Rubery, 2015), this includes only children aged 18 or younger. Some papers define "children" more strictly – women must have children younger than 18 who are also currently *living* with them. However, many parents migrate for work in South Africa, and so do not live with their children. Since having children may affect a woman's decision to seek work, including these women as "mothers" in the sample is important. Most women in South Africa do not have more than three children: 85%

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[8] This includes African women aged between 20-44 only.

[9] The full question was "How much did you earn at your main job before any deductions for tax, medical aid or pension?"

of women in the sample have three or fewer children. I also include a variable for the number of non-biological children in each household. In Appendix A7, a breakdown of the number of children women report to have given birth to in each wave is presented. I also include a variable *non-biological children,* which includes the number of non-biological children living in a household with a woman.

Other independent variables in this analysis include human capital variables such as years of education and weekly hours worked. Weekly hours worked is a continuous variable which includes hours worked in both individuals' first and second most important wage jobs. This is to ensure consistency with the independent variable, monthly take home pay, which includes monthly earnings for both individuals' first and second jobs (Brophy et al., 2018).

I also include occupation status as a categorical variable with nine categories. Occupations in NIDS are classified by ISCO status (Brophy et al., 2018), a standardized measure of occupation employed by the International Labour Organization. The nine categories used in the variable include: Managers, Professionals, Technicians and Associated Professionals, Clerical Support Workers, Service and Sales Workers, Agricultural, Forestry and Fishery Workers, Craft and related trades Workers, Plant and Machine Operators and Elementary Workers[10]. Women who were in the armed forces were excluded. I also include a dummy variable indicating whether women belong to a union or not. Unions exert substantial power in South Africa, and researchers have found that workers belonging to a union in South Africa enjoy a large wage premium (Bhorat et al., 2009).

I include a variable for marital status, where women are defined as either married, living with a partner, widowed, divorced, or never married. Finally, I include a variable on where women live – urban areas, traditional (rural) areas, or on farms.

Table 14 below presents key characteristics for four groups of African women: women without children in column (1), women with children up to the age of 18 in column (2), women with at least one young child, up to the age of six in column (3), and women with only older children, aged between 7-18 in column (4), pooled across all five waves of NIDS. Previous studies have shown that there is often a difference in the wage penalty experienced by mothers with young children, compared to the penalty experienced by mothers with older children (for example, see Aguero et al., 2020). Women who did not have data on whether they had given birth were excluded from the sample, as well as women who had no children aged 18 or younger. This leaves a sample size of 8 677 African women. Since Table 14 includes both CSM and TSM women, I redo Table 14 including only CSM women. This table can be found in Appendix A7. Excluding TSM women does not substantially alter the results.

The average age of a mother in South Africa is 33, and she has 2.26 children on average. Over 60% of mothers have a maximum of two children – only 15% of mothers have four or more children. The average number of non-biological children living in a household is less than one, in all categories. Comparing (1) and (2), childless women, on average, earn more than mothers. While childless women are younger – on average, aged 28 – they are also

[10] This includes cleaners, mining, construction, and transport labourers, and refuse workers (International Labour Organization, 1993).

more educated, less likely to work part-time and employed in more skilled occupations. Childless women have, on average, a year's more education than mothers. Mothers are more likely to be employed in elementary occupations: 37% of mothers are employed in elementary occupations, compared with 21% of childless women. Childless women are also more likely to belong to a union and to live in urban areas. Comparing columns (3) and (4), most variables remain relatively similar. However, mothers with young children do earn less, on average, than mothers with older children. This may be partly explained by the fact more mothers of young children work part-time than mothers of older children but may also be due to mothers with older children being older and having more labour market experience.

Table 14: Key Characteristics for Women aged between 20-44 by Motherhood Status

VARIABLES	(1)	(2)	SE of Difference between (1) and (2)	(3)	(4)	SE of Difference between (3) and (4)
Monthly Take Home Pay (R)	5664,16	4486,13	**489,22 *****	4242,12	4819,37	**247,33 *****
Age (years)	27,52	33,34	**0,270 *****	31,19	36,39	**0,183*****
Number of Children	-	2,26	**0,025 *****	2,35	2,14	**0,039*****
Categorical Children						
1	-	32,33	**0,008 *****	29,76	35,96	**0,014*****
2	-	33,70	**0,007 *****	33,86	33,48	**0,012*****
3	-	19,21	**0,006 *****	19,41	18,93	**0,010*****
4+	-	14,76	**0,007 *****	16,97	11,63	**0,007*****
Number of non-biological children	0,171	0,124	**0,192 *****	0,147	0,092	0,015
Marital Status						
Married	10,32	25,75	**0,012*****	24,19	27,95	0,012
Living with Partner	5,49	10,70	**0,009*****	12,86	7,66	**0,008*****
Widow	0,90	2,95	**0,004*****	1,50	4,99	**0,004*****
Divorced	0,72	2,83	**0,003*****	1,42	4,83	**0,003*****
Never Married	82,57	57,77	**0,020*****	60,02	54,58	0,015
Years of Education	11,60	10,68	**0,080*****	10,80	10,50	0,072
Part-time work	12,12	14,75	**0,067*****	15,02	14,36	0,007
Hours worked (per month)	39,55	39,29	0,831	39,42	39,13	0,731
Occupation						
Manager	6,00	3,37	0,017	3,36	3,38	0,009
Professional	17,73	14,75	0,025	13,08	17,04	0,018
Technician	6,51	4,40	0,014	4,92	3,69	0,008
Clerk	12,59	8,51	**0,019****	8,58	8,41	0,014
Services and Sales	26,24	24,82	0,031	26,41	22,63	0,021
Agriculture	0,02	0,38	**0,001*****	0,31	0,48	0,001
Artisan	6,67	4,91	0,017	5,11	4,64	0,009
Machine Operator	2,81	2,01	0,013	2,27	1,66	0,006
Elementary	21,42	36,85	**0,026*****	35,95	38,08	0,023
Union Member	30,01	24,98	**0,028****	24,08	26,21	0,021
Geography						
Traditional	19,74	28,33	**0,018*****	28,13	28,60	**0,012*****

Urban	78,40	66,62	**0,018*** **	67,10	65,95	**0,013*** **
Farm	1,85	5,05	**0,006*** **	4,77	5,45	0,007
N	**1 008**	**7 669**		**4 564**	**3 105**	

Data Source: NIDS Wave 1-5 Pooled Data. Data is weighted using calibrated cross-section weights. Weighting accounts for complex sample design. Column (1) refers to childless women. Column (2) refers to all mothers. Column (3) refers to mothers with at least one child young child (aged between 0-6 years old). Column (4) refers to mothers of only older children (aged between 7-18 years old). Unless stated otherwise, all variables are in %. A woman is defined as a mother if she has given birth and at least one of her children is aged 18 or younger. *** p<0.01, **p<0.05, *p<0.1.

Since I will be using the NIDS dataset as a panel, I redo the key characteristics of African women only for women who are employed in more than one wave. This is shown in Table 15 below. Table 15 shows similar trends to Table 14: non-mothers have average higher wages, higher levels of education and higher union participation than mothers.

Table 15: Key Characteristics for Women Employed in at least two Waves aged between 20-44 by Motherhood Status

VARIABLES	**(1)**	**(2)**	**SE of Difference between (1) and (2)**	**(3)**	**(4)**	**SE of Difference between (3) and (4)**
Monthly Take Home Pay (R)	5192,80	4652,28	**449,11 *** **	4452,55	4962,67	**243,27 *** **
Age (years)	27,35	32,97	**0,313 *** **	31,52	35,36	**0,197 *** **
Number of Children	-	2,20	**0,039 *** **	2,31	2,02	**0,042 *** **
Categorical Children						
1	-	32,61	**0,009 *** **	29,39	37,91	**0,015 *** **
2	-	34,06	**0,008 *** **	34,17	33,89	**0,012 *** **
3	-	20,74	**0,007 *** **	20,82	20,62	**0,011 *** **
4+	-	12,59	**0,008 *** **	15,63	7,58	**0,008 *** **
Number of non-biological children	0,209	0,120	**0,025 *** **	0,141	0,085	0,018
Marital Status						
Married	7,02	25,45	**0,014 *** **	23,86	28,22	0,012
Living with Partner	5,18	10,24	**0,009 *** **	12,03	7,11	**0,009 *** **
Widow	1,14	2,71	**0,004 *** **	1,19	5,36	**0,004 *** **
Divorced	0,25	2,10	**0,003 *** **	1,00	4,02	**0,004 *** **
Never Married	86,14	59,50	**0,017 *** **	61,92	55,28	0,015
Years of Education	11,73	10,93	**0,091 *** **	11,09	10,67	0,086
Part-time work	10,09	16,64	**0,007 *** **	15,57	16,82	0,007
Hours worked (per month)	39,55	39,29	0,884	39,42	39,13	0,778
Occupation						
Manager	4,65	3,64	0,017	3,76	3,46	0,010
Professional	20,33	13,94	0,026	12,41	16,31	0,018
Technician	5,44	4,58	0,015	5,56	3,06	0,008
Clerk	13,33	9,48	0,021	9,65	9,20	0,015
Services and Sales	28,76	25,80	0,034	26,80	24,23	0,023
Agriculture	0	0,43	**0,001 *** **	0,21	0,78	0,001
Artisan	4,93	5,11	0,017	5,11	5,12	0,010

Machine Operator	2,75	1,88	0,014	1,76	2,08	0,007
Elementary	19,80	35,14	**0,028 *****	34,74	35,76	0,023
Union Member	31,22	27,52	0,032	26,90	28,48	0,022
Geography						
Traditional	14,52	25,50	**0,019 *****	24,13	27,76	**0,014 ****
Urban	83,55	69,87	**0,020 *****	72,09	66,21	**0,015 ***
Farm	1,94	4,63	**0,006 *****	3,78	6,03	0,005
N	**316**	**2 401**		**1 506**	**895**	

Data Source: NIDS Wave 1-5 Pooled Data. Data is weighted using calibrated panel weights. Weighting accounts for complex sample design. Column (1) refers to childless women. Column (2) refers to all mothers. Column (3) refers to mothers with at least one child young child (aged between 0-6 years old). Column (4) refers to mothers of only older children (aged between 7-18 years old). Unless stated otherwise, all variables are in %. A woman is defined as a mother if she has given birth and at least one of her children is aged 18 or younger. *** p<0.01, **p<0.05, *p<0.1.

Table 14 and 15 both show that women who are not mothers earn more than mothers. However, as shown in the previous section, the *number* of children women have given birth to also affects labour market outcomes. To account for this, Table 16 below presents the changes in the mean and median monthly take-home pay for women by changes in the number of children they have given birth to, using NIDS as a panel dataset to compare earnings between waves.

The table shows that any "motherhood" penalty may not be distributed equally among mothers – mothers with more children may experience a larger wage gap than mothers with fewer children. Looking first at the changes in mean take home pay, women without children experience a R1 673 increase in earnings, perhaps representing human capital gains over two years. For women with children, for example, women with one child, this increase in earnings is smaller (R1 164 between waves), suggesting a deficit in mother's earning trajectory. This deficit exists across all numbers of children but is larger for women with more children. However, these average changes may be skewed by a few large negative or positive changes in income between waves. To account for this, the median changes in take home pay are presented below too.

The median changes in earnings present a slightly different picture: all women, regardless of the number of children they have, experience higher median earnings, on average, between waves. However, the change in earnings differs markedly by the number of children women have; women who remain childless see an average increase in median earnings of R1 196, while women who go from two to three or more children see an average median increase in earnings of R56, again suggesting a deficit in earnings for mothers, compared with childless women.

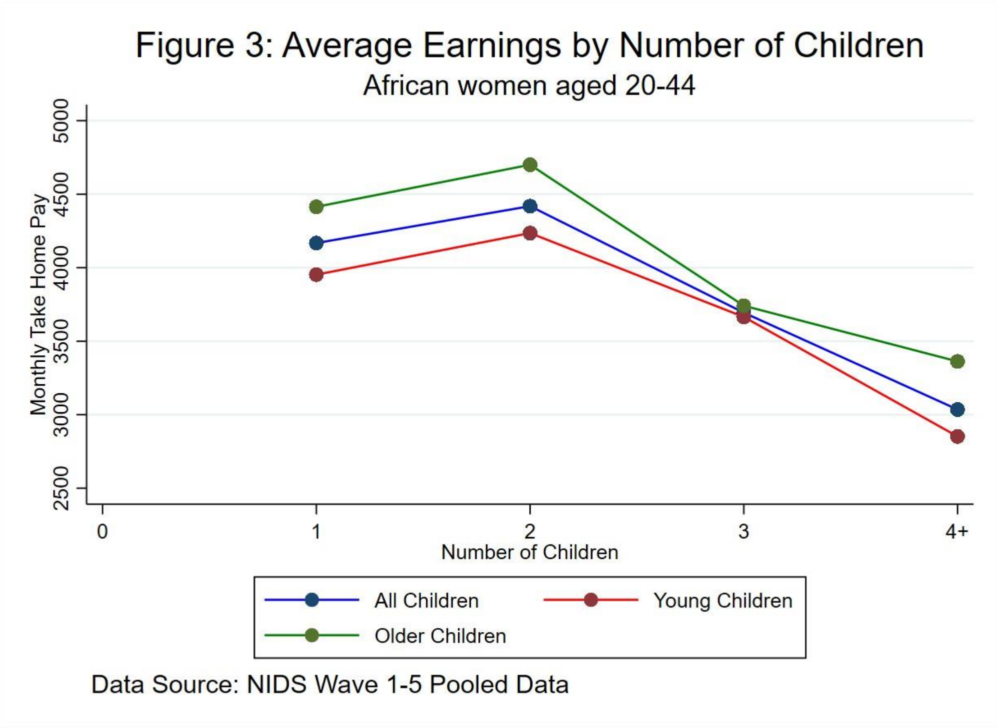
Table 16: Change in Take Home Pay by Changes in Number of Children

	Mean Take Home Pay	**Mean Take Home Pay (T+1)**	**Change in Mean Take Home Pay**
0-0	5722,31	7395,45	1673,14
0-1	4168,13	5332,55	1164,42
1-2	5881,07	6460,46	579,39
2-3+	5355,66	3984,53	-1 371,13

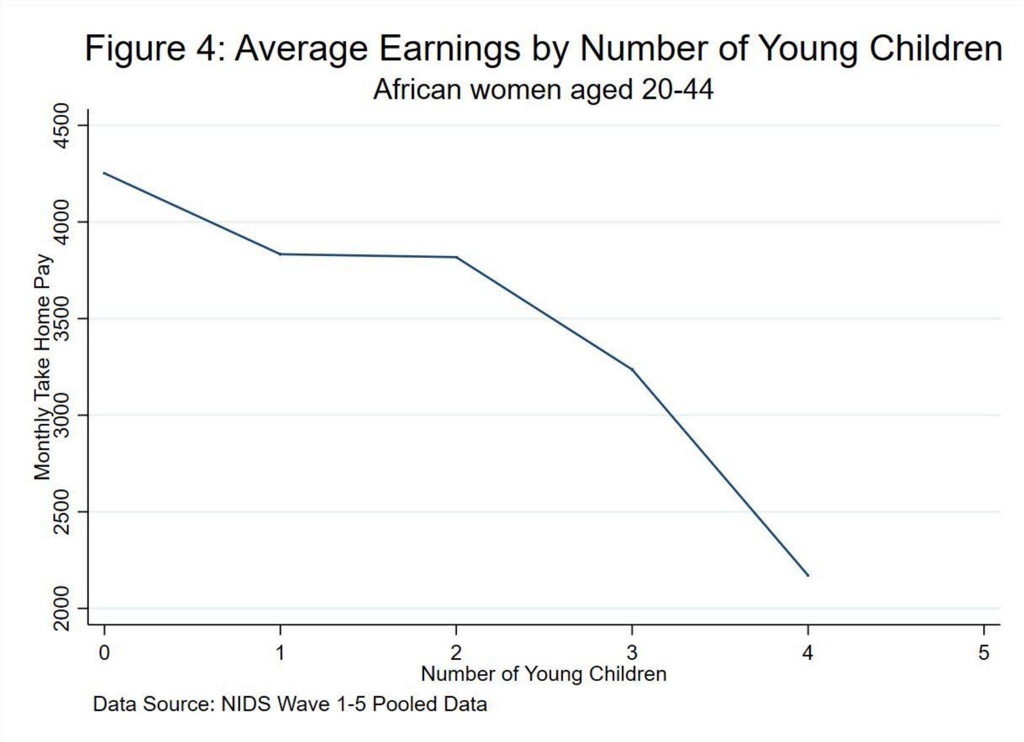
	Median Take Home Pay	Median Take Home Pay (T+1)	Change in Median Take Home Pay
0-0	3916,08	5112,36	1196,28
0-1	3146,07	3629,42	483,35
1-2	3740,65	4157,30	416,65
2-3+	2808,99	2865,33	56,34

Data Source: NIDS Wave 1-5 Panel. Data is weighted using panel weights to account for complex sample design and attrition. (T+1) refers to data collected one wave after the initial wave.

It is likely that the age of children also affects mother's earnings. Women with younger children may be more likely to work part-time, or select a job with flexible working hours, which could affect their monthly earnings. Figure 3 below presents the average earnings for mothers only, by the age of their children. The graph reveals two important facts: first, mothers of young children earn less, on average, than mothers of older children, and second, women with more children earn less, on average, than women with fewer children. This is consistent with the findings of previous studies on the motherhood wage penalty in developing countries (Aguero et al., 2020).



Finally, the number of young children may also matter for mother's earnings. Mothers who have multiple young children may struggle to balance work and motherhood, which may be correlated to earnings. Figure 4 presents the average Take Home Pay for mothers by the number of young children they have. The graph includes only mothers – with zero young children indicating that a mother only has older children (aged between 7-18). Figure 4 shows that earnings are negatively correlated with the number of young children a mother has – average earnings are halved for mothers with four young children, compared to mothers with no young children. Both Figure 3 and Figure 4 are recreated in the Appendix (appendices A8 and A9 respectively) to ensure that the sample of CSM women is similar to the sample of both CSM and TSM women.



This analysis shows that not only does motherhood affect women's earnings, but that the number and age of children is also significant in determining earnings. However, descriptive analysis can only infer correlations between earnings and motherhood. To better understand the mechanisms affecting women's earnings and whether there is a causal relationship between children and women's earnings, in the next section, I study the relationship between earnings and children using regression analysis.

5.2. Econometric Analysis

In this study, I will use the following model to study the effects of motherhood on earnings:

$$\log(earnings)_i = \beta 0 + \beta 1(kids)_i + \beta 2(union)_i + \beta 3(nobiokids)_i + \gamma 1(age)_i + \gamma 2(age^2)_i + \delta 1(marstat2)_i + \delta 2(marstat3)_i + \delta 3(marstat4)_i + \delta 4(marstat5)_i + \theta 1(geo2)_i + \theta 2(geo3)_i + \vartheta 1(occ2)_i + \vartheta 2(occ3)_i + \vartheta 3(occ4)_i + \vartheta 4(occ5)_i + \vartheta 5(occ6)_i + \vartheta 6(occ7)_i + \vartheta 7(occ8)_i + \vartheta 8(occ9)_i + \tau(educ)_i + \varphi(hours)_i + \omega 1(wave2) + \omega 2(wave3) + \omega 3(wave4) + \omega 4(wave5) + u_i \quad (9)$$

Where log(earnings) is the log value of monthly take-home pay. I define the key independent variable *kids* as the number of biological children, who are aged 18 or younger, a woman has given birth to. Given that most women in South Africa are mothers (as shown in the previous section), it is more interesting to look at the effect that additional children have on women's earnings rather than a binary change to motherhood. This definition of motherhood also follows the work of previous researchers (for example, see England et al., 2016 and Aguero et al., 2020). *Nobiokids* is the number of non-biological children in a household. *Age* and age^2 are continuous variables indicating a women's age, and the square of age respectively. *Union* is a dummy variable which indicates whether a woman belongs to a union or not. *Marstat2-5* are categorical variables indicating marital status (with the base category *married* excluded to prevent collinearity). Likewise, *geo2-3* refers to where women live in South Africa: traditional areas (base category), farmlands, or urban areas. *Occ2-9* is another categorical variable indicating what occupation women are employed in, with the base category *Manager* excluded. I include a continuous variable *hours* which indicates the number of hours a woman works every month in her primary and secondary occupation. This is to ensure consistency with the independent variable *Monthly Take Home Pay*, which includes earnings from both primary and secondary occupations.

Differences in human capital accumulation, such as education, have explained parts of the motherhood penalty in other countries (for example, see Budig and England, 2001). Women who choose to invest in human capital – for example, through attending tertiary education, participating in full-time employment, and working continuously (thus gaining work experience) may choose to have fewer children (Budig and England, 2001). The most popular measure of human capital accumulation is education, and there is a broad consensus among researchers that as education increases, earnings increase. In this study I code education as a continuous variable, measuring the years of education a woman has received. Since years of education is a continuous variable, I also include a squared *years of education* variable.

Many studies also include years of experience to account for human capital differences (for example, see Budig and England, 2001). Unfortunately, in the NIDS dataset, questions on work experience were not asked. Some studies have turned to potential work experience (Mincer, 1974), which is calculated by subtracting years of education and five additional years from the age of respondent. However, since this proxy is highly correlated with age, I decided against including it in the equation. Moreover, this proxy assumes that individuals can find consistent employment as soon as they have finished their education. Given South Africa's high unemployment rate, and the low proportion of employed women, this is not a reasonable assumption to make. Instead, I include the number of hours a woman works per week. Finally, $wave2 - 5$ are categorical variables, controlling for time. The base category, *wave1* is excluded.

However, the estimated coefficients outlined above may be biased due to unobserved heterogeneity. If mothers and non-mothers differ in unobserved ways (for example, if non-mothers are more ambitious, or have greater ability or productivity), and these differences are correlated with earnings, as many researchers believe may be the case, or mothers with more children differ from those with fewer children, then the OLS coefficients will be biased (Wooldridge, 2015). Controlling for unobserved heterogeneity presents additional econometric challenges, and I account for this by using both fixed effects and first difference regression analysis and comparing the results to OLS regression analysis.

The fixed effects model is shown in equation (10) below. All variables remain the same as in the OLS model.

However, the fixed effects estimator controls for unobserved, time invariant differences, αi. Assuming that any unobserved differences between mothers and non-mothers remain constant over time, the estimator will remove these characteristics, effectively controlling for differences between mothers and non-mothers that arise from time invariant characteristics.

$$\log(earnings)_{it} = \beta 0 + \beta 1(kids)_{it} + \beta 2(union)_{it} + \beta 3(nobiokids)_{i} + \gamma 1(age)_{it} + \gamma 2(age^{2})_{it} + \delta 1(marstat2)_{it} + \delta 2(marstat3)_{it} + \delta 3(marstat4)_{it} + \delta 4(marstat5)_{it} + \theta 1(geo2)_{it} + \theta 2(geo3)_{it} + \vartheta 1(occ2)_{it} + \vartheta 2(occ3)_{it} + \vartheta 3(occ4)_{it} + \vartheta 4(occ5)_{it} + \vartheta 5(occ6)_{it} + \vartheta 6(occ7)_{it} + \vartheta 7(occ8)_{it} + \vartheta 8(occ9)_{it} + \tau 1(educ)_{it} + \tau 2(educ^{2})_{it} + \varphi(hours)_{it} + \omega 1(wave2)_{t} + \omega 2(wave3)_{t} + \omega 3(wave4)_{t} + \omega 4(wave5)_{t} + a_{i} + u_{it} \tag{10}$$

Table 17 below presents the OLS, fixed effects and first difference output for the motherhood penalty. Consistent with the literature, children are negatively correlated with mother's earnings. The difference in sample size between the OLS and fixed effects results are due to the OLS results including both CSMs and TSMs, while the first difference and fixed effects results include only CSMs. The reduction in the sample size between the fixed effects and first differenced sample sizes is because the fixed effects sample reported by Stata includes women who are observed once in the panel, whereas the first difference sample only includes women who are observed in at least two waves in the panel. To ensure that the OLS results can be compared accurately to the fixed effects and first difference results, I repeat the OLS regression using only CSMs in the appendix. The results of the OLS regression with only CSMs can be found in Column (A1) of Appendix A10. The results do not change substantially when including only CSMs. As an additional robustness check, I redo Column (1) of Table 17, including only women who are employed in more than one Wave of NIDS. This is to create a comparable sample to the sample used in Columns (2) and (3). The results do not change substantially, and similar trends can be seen in both OLS analyses. The repeated OLS regression can be found in Appendix A11.

Across all three estimators, having an additional child reduces average earnings. The size of the penalty differs across the estimators and is statistically significant only in the OLS and first difference estimators.

In the OLS estimator, having one more child is associated with a decline in women's earnings, on average, by 4.17%. Having an additional non-biological child living in the household reduces earnings, on average, by 3.5%. Controlling for unobserved differences between mothers and non-mothers using fixed effects reduces the significance of the penalty. The size of the coefficient also remains relatively similar. Fixed effects and first differencing account for unobserved heterogeneity by removing any time invariant differences in the error term, which could affect earnings (Wooldridge, 2015). If the estimators were the same in Table 17, we could conclude that there are no time invariant characteristics in the error term which are correlated with the explanatory variables affecting wages. The reduction in the statistical significance of the wage penalty in the fixed effects estimator could be because the estimators have successfully removed some part of the time invariant unobserved component in the error term.

The first difference estimated coefficients (showing the difference between the current and previous wave), in

Column (3), present a different story. Here, the size of the wage penalty is doubled compared with OLS: one more child is associated with an average decrease in wages of 11%, significant at the 5% level, holding all else constant. It is often difficult to discern whether to use first difference or fixed effects results, and for this reason, many researchers report both (for example, see Gough and Noonan, 2013).

In all three estimators, occupation is significant in affecting earnings. This is consistent with the literature. Age is also highly significant and, up to a certain age, positively correlated with earnings in all the estimators. I experimented with not including age in the fixed effects regression as, in theory, any variables that are time invariant, or which change consistently with time should not be included in a fixed effects estimator. However, I found that not including age meant additional children were *positively* correlated with women's earnings. Given that employment and earnings prospects are so highly and positively correlated with age in South Africa (Branson, 2004), it is likely that this positive relationship between children and earnings has less to do with children, and more to do with age: older women are likely to have more children, but also earn higher wages, than young women. Thus, I decided it was important to include age in the fixed effects and first difference models. This is also consistent with other research done on the motherhood penalty (for example, see Avellar and Smock, 2004 and Aguero et al., 2020). Moreover, the wave intervals in NIDS are not exactly two years, which means there is some variation in age independent of time.

A final reason for the reduction in the significance of the fixed effects coefficients could be that there is not sufficient movement in the *kids* variable between waves. Without enough variation in the variable *kids* between waves, the estimated coefficient $\beta 1$ may reduce in significance (Wooldridge, 2015). However, as shown in Table 9 in the previous section, there is substantial movement in the number of children women give birth to over time.

Table 17: The Motherhood Wage Penalty

	(1) OLS	**(2) Fixed Effects**	**(3) First Difference**
Number of Children	**-0.0417*** **	-0.0521	**-0.112** **
	(0.0110)	(0.0354)	**(0.0489)**
Non-biological Children	**-0.0350* **	0.0167	0.0443
	(0.0182)	(0.0337)	(0.0395)
Age	**0.0829*** **	**0.164*** **	**0.137** **
	(0.0221)	**(0.0474)**	**(0.0616)**
Age Squared	**-0.00110*** **	**-0.00157*** **	-0.00115
	(0.000329)	**(0.000507)**	(0.000766)
Education	**-0.0819*** **	0.0467	0.0484
	(0.0211)	(0.0719)	(0.0704)
Education Squared	**0.00995*** **	-9.79e-05	-0.00142
	(0.00139)	(0.00317)	(0.00323)
Hours worked	**0.169*** **	**0.0745*** **	**0.0579* **
	(0.0267)	**(0.0271)**	**(0.0309)**
Marital Status			

Base: Married			
Living with Partner	**-0.139*** **	**-0.137** **	-0.0878
	(0.0490)	**(0.0649)**	(0.0746)
Divorced	-0.00652	**-0.284** **	**-0.338*** **
	(0.0963)	**(0.124)**	**(0.112)**
Widowed	0.186**	0.0836	0.00540
	(0.0726)	(0.0971)	(0.0940)
Never Married	**-0.0930*** **	**-0.138** **	**-0.185** **
	(0.0350)	**(0.0690)**	**(0.0786)**
Union	**0.409*** **	**0.124*** **	**0.124** **
	(0.0400)	**(0.0447)**	**(0.0562)**
Occupation			
Base: Manager			
Professional	-0.0181	-0.153	-0.154
	(0.0946)	(0.109)	(0.127)
Technician	-0.125	-0.156	-0.186
	(0.110)	(0.108)	(0.132)
Clerk	-0.0799	-0.144	-0.150
	(0.0875)	(0.125)	(0.150)
Service and Sales	**-0.523*** **	**-0.174* **	-0.173
	(0.0852)	**(0.0987)**	(0.128)
Agriculture	**-0.812*** **	**-0.536* **	**-0.606* **
	(0.164)	**(0.315)**	**(0.358)**
Artisan	**-0.497*** **	-0.170	**-0.325** **
	(0.0971)	(0.123)	**(0.154)**
Machine Operator	**-0.549*** **	-0.249	**-0.477** **
	(0.125)	(0.207)	**(0.226)**
Elementary	**-0.676*** **	**-0.226** **	**-0.325** **
	(0.0880)	**(0.107)**	**(0.130)**
Geography			
Base: Traditional			
Urban	**0.253*** **	0.00957	-0.118
	(0.0408)	(0.0648)	(0.114)
	0.143 **	0.103	0.176
Farms	**(0.0601)**	(0.102)	(0.127)
Wave			
Base: 1			
2	**0.107** **	0.115	0.0940
	(0.0441)	(0.104)	(0.123)
3	**0.192*** **	0.0979	0.0957
	(0.0400)	(0.176)	(0.217)
4	**0.218*** **	0.114	0.121
	(0.0367)	(0.266)	(0.318)
5	**0.221*** **	0.0539	0.0495
	(0.0372)	(0.348)	(0.422)
Constant	**5.674*** **	**3.895*** **	
	(0.343)	**(1.227)**	

Observations	6 084	4,623	1,798
Number of pid		2,464	
R-Squared	0.484	0.183	0.086

Standard errors in parentheses. *** p<0.01, **p<0.05, *p<0.1. Column (1) includes OLS results. Column (2) includes fixed effects results, and Column (3) includes first difference results. OLS regression is weighted using cross-section weights to account for complex survey design. Fixed effects and first difference regressions are weighted using panel weights, which account for attrition and complex survey design.

As I showed in the previous section, it is unlikely that "motherhood" affects women in the same way. The age of children, and the number of children a woman has, is likely to affect women's ability to work, and thus wages. In the previous model, including *kids* as a continuous variable assumes that a linear increase in the number of children results in the same reduction in wages. Under this assumption, for example, a woman going from zero to one child would experience the same reduction in wages as a woman going from three to four children.

This assumption may be unrealistic, and for this reason I adapt equation (10), replacing *kids* with *kidscat*, a categorical variable indicating whether a woman has 0, 1, 2, 3, or 4 or more children. Since most women in South Africa have three or fewer children, grouping all women with more than three children together made sense. The updated model (11) is described below.

$$\log(earnings)_{it} = \beta 0 + \rho 1(kidscat1)_{it} + \rho 2(kidscat2)_{it} + \rho 3(kidscat3)_{it} + \rho 4(kidscat4)_{it} + \beta 2(union)_{it} + \beta 3(nobiokids)_{i} + \gamma 1(age)_{it} + \gamma 2(age^2)_{it} + \delta 1(marstat2)_{it} + \delta 2(marstat3)_{it} + \delta 3(marstat4)_{it} + \delta 4(marstat5)_{it} + \theta 1(geo2)_{it} + \theta 2(geo3)_{it} + \vartheta 1(occ2)_{it} + \vartheta 2(occ3)_{it} + \vartheta 3(occ4)_{it} + \vartheta 4(occ5)_{it} + \vartheta 5(occ6)_{it} + \vartheta 6(occ7)_{it} + \vartheta 7(occ8)_{it} + \vartheta 8(occ9)_{it} + \tau 1(educ)_{it} + \tau 2(educ^2)_{it} + \varphi(hours)_{it} + \omega 1(wave2)_{t} + \omega 2(wave3)_{t} + \omega 3(wave4)_{t} + \omega 4(wave5)_{t} + a_i + u_{it} \quad (11)$$

The results of (11) are presented in Table 18 below. In the OLS results, having one child results in a statistically significant wage penalty of 12.9%, ceteris paribus. However, having a second child does not result in an additional penalty – on the contrary, mothers with two children experience a slightly lower wage penalty of 12.2%, compared to women with no children. For women with three or more children, the penalty increases: women with three children experience an average reduction in earnings of 16.2% compared to women with no children, and women with four or more children experience a reduction in earnings of 24%, ceteris paribus.

The unequal penalties experienced by women with differing numbers of children is shown again in the fixed effects and first difference estimators. In the fixed effects estimator, having one or two children is *positively* correlated with earnings, compared to women with no children, although these results are not statistically significant. Once women have three or more children however, average earnings reduce, although these results are also not statistically significant. This could be the result of measurement error (discussed in Section 2), which is one of the drawbacks of using fixed effects analysis. Alternatively, since fixed effects does eliminate bias, the lack of statistically significant results could also indicate that the effect of additional children does not significantly affect women's earnings.

However, the first differenced results show statistically significant differences in earnings for women with three or more. Women with three children earn, on average, 34% less than women with no children, while women with four or more children earn, on average, over 40% less than women with no children.

Consistent with the literature, age, education, hours worked, and union membership remain significant in affecting women's wages. The exception here is education in the first difference estimator, which is not statistically significant. This is likely because there was insufficient movement in education levels between subsequent waves. Finally, as with the OLS estimator in Table 16, the OLS results below include both CSMs and TSMs. I repeat the regression using only CSMs in Column (A2) in Appendix A10, showing no substantial difference when TSMs are excluded.

Table 18: Motherhood Wage Penalty with Categorial Kids

	(1) OLS	**(2) Fixed Effects**	**(3) First Difference**
Number of Children			
Base: 0			
1	**-0.129*** **	0.0112	-0.0237
	(0.0428)	(0.0646)	(0.0744)
2	**-0.122*** **	0.0162	-0.138
	(0.0456)	(0.0912)	(0.106)
3	**-0.162*** **	-0.133	**-0.346** **
	(0.0526)	(0.112)	**(0.163)**
4	**-0.240*** **	-0.197	**-0.435** **
	(0.0564)	(0.143)	**(0.197)**
Non-biological Children	**-0.0337* **	0.0156	0.0440
	(0.0183)	(0.0336)	(0.0395)
Age	**0.0858*** **	**0.155*** **	**0.130** **
	(0.0226)	**(0.0481)**	**(0.0623)**
Age Squared	**-0.00115*** **	**-0.00147*** **	-0.00110
	(0.000336)	**(0.000521)**	(0.000781)
Education	**-0.0800*** **	0.0521	0.0568
	(0.0212)	(0.0720)	(0.0725)
Education Squared	**0.00987*** **	-0.000325	-0.00183
	(0.00139)	(0.00316)	(0.00330)
Parttime	**0.169*** **	**0.0734*** **	**0.0574* **
	(0.0270)	**(0.0271)**	**(0.0309)**
Marital Status			
Base: Married			
Living with Partner	**-0.138*** **	**-0.129* **	-0.0876
	(0.0485)	**(0.0662)**	(0.0749)
Divorced	-0.00628	**-0.279** **	**-0.337*** **
	(0.0965)	**(0.124)**	**(0.111)**
Widowed	**0.185** **	0.0876	0.00577

	(0.0725)	(0.0975)	(0.0935)
Never Married	**-0.0898****	**-0.131***	**-0.185****
	(0.0355)	**(0.0678)**	**(0.0791)**
Union	**0.411*****	**0.121*****	**0.124****
	(0.0404)	**(0.0448)**	**(0.0565)**
Occupation			
Base: Manager			
Professional	-0.0175	-0.145	-0.148
	(0.0944)	(0.109)	(0.127)
Technician	-0.129	-0.152	-0.183
	(0.109)	(0.108)	(0.130)
Clerk	-0.0745	-0.138	-0.148
	(0.0870)	(0.125)	(0.149)
Service and Sales	**-0.520*****	**-0.173***	-0.170
	(0.0848)	**(0.0980)**	(0.127)
Agriculture	**-0.799*****	**-0.528***	-0.595
	(0.165)	**(0.318)**	(0.361)
Artisan	**-0.494*****	-0.170	**-0.320****
	(0.0965)	(0.124)	**(0.154)**
Machine Operator	**-0.548*****	-0.252	**-0.475****
	(0.125)	(0.205)	**(0.228)**
Elementary	**-0.676*****	**-0.222****	**-0.320****
	(0.0870)	**(0.107)**	**(0.131)**
Geography			
Base: Traditional			
Urban	**0.251*****	0.00891	-0.120
	(0.0406)	(0.0647)	(0.113)
Farms	**0.145****	0.0971	0.174
	(0.0600)	(0.102)	(0.127)
Wave			
Base: 1			
2	**0.106****	0.116	0.102
	(0.0445)	(0.104)	(0.123)
3	**0.191*****	0.105	0.113
	(0.0402)	(0.176)	(0.218)
4	**0.217*****	0.123	0.145
	(0.0368)	(0.266)	(0.319)
5	**0.222*****	0.0644	0.0805
	(0.0374)	(0.349)	(0.423)
Constant	**5.666*****	**3.973*****	
	(0.348)	**(1.224)**	
Observations	6 084	4 623	1 789
Number of pid		2 464	
R-Squared	0.485	0.185	0.087

Standard errors in parentheses. *** p<0.01, **p<0.05, *p<0.1. Column (1) includes OLS results. Column (2) includes fixed effects results, and Column (3) includes first difference results. OLS regression is weighted using cross-section weights to account for complex survey design. Fixed effects and first difference regressions are weighted using panel weights, which account for attrition and complex survey design.

Finally, according to Becker (1985), a key component of the disparity in earnings between mothers and non-mothers are household and childcare responsibilities. Women who have children to care for are more likely to put less effort into labour market responsibilities, to save energy for childcare responsibilities (Becker, 1985). Since young children (aged between 0-6) demand more attention and care than older children, it is plausible that mothers of young children will exhibit a further penalty compared to mothers of older children (Aguero et al., 2020). I adapt Equation (10), replacing *kids* as the key independent variable with two continuous variables: *Young Children*, and *Older Children* which indicate the number of young children (aged between 0-6) and older children (7–18-year-olds) a woman has. The updated equation (12) is shown below.

$$\log(earnings)_{it} = \beta 0 + \beta 1(youngkid)_{it} + \beta 2(oldkid)_{it} + \beta 3(union)_{it} + \beta 4(nobiokids)_i + \gamma 1(age)_{it} + \gamma 2(age^2)_{it} + \delta 1(marstat2)_{it} + \delta 2(marstat3)_{it} + \delta 3(marstat4)_{it} + \delta 4(marstat5)_{it} + \theta 1(geo2)_{it} + \theta 2(geo3)_{it} + \vartheta 1(occ2)_{it} + \vartheta 2(occ3)_{it} + \vartheta 3(occ4)_{it} + \vartheta 4(occ5)_{it} + \vartheta 5(occ6)_{it} + \vartheta 6(occ7)_{it} + \vartheta 7(occ8)_{it} + \vartheta 8(occ9)_{it} + \tau 1(educ)_{it} + \tau 2(educ^2)_{it} + \varphi(hours)_{it} + \omega 1(wave2)_t + \omega 2(wave3)_t + \omega 3(wave4)_t + \omega 4(wave5)_t + a_i + u_{it} \quad (12)$$

The results of equation (12), shown in Table 19 below show mixed results. In the OLS estimator, having one additional young child is associated with a higher average wage penalty compared to having an additional older child.

When controlling for unobserved heterogeneity using fixed effects and first difference, the effect of older children becomes *positively* correlated with earnings, while an additional young child is negatively correlated with earnings – although these results are only statistically significant for first differencing. This result is consistent with the findings of other researchers who have studied the motherhood wage penalty in developing countries: having older children may make it easier for mothers to seek work, as their children can partake in household chores, and looking after younger siblings (Aguero et al., 2020).

Table 19: Motherhood Wage Penalty with Number of Young and Older Children

	(1) **OLS**	**(2)** **Fixed Effects**	**(3)** **First Difference**
Young Children	**-0.0497*** **	-0.0209	**-0.0708***
	(0.0171)	(0.0327)	**(0.0392)**
Older Children	**-0.0380** **	0.0471	3.64e-05
	(0.0153)	(0.0465)	(0.0460)
Non-biological Children	**-0.0343***	0.0157	0.0450
	(0.0181)	(0.0335)	(0.0396)
Age	**0.0955*** **	**0.136*** **	**0.129** **
	(0.0226)	**(0.0414)**	**(0.0646)**
Age Squared	**-0.00134*** **	**-0.00120** **	-0.00109
	(0.000337)	**(0.000480)**	(0.000802)
Education	**-0.0806*** **	0.0480	0.0489
	(0.0212)	(0.0738)	(0.0700)

Education Squared	**0.00997*** **	-0.000109	-0.00145
	(0.00140)	(0.00325)	(0.00324)
Hours Worked	**0.168*** **	**0.0747*** **	**0.0568** *
	(0.0265)	**(0.0271)**	**(0.0312)**
Marital Status			
Base: Married			
Living with Partner	**-0.139*** **	**-0.130** **	-0.0862
	(0.0491)	**(0.0643)**	(0.0741)
Divorced	-0.0129	**-0.280** **	**-0.338*** **
	(0.0954)	**(0.121)**	**(0.111)**
Widowed	**0.182** **	0.0972	0.00477
	(0.0723)	(0.0986)	(0.0928)
Never Married	**-0.0921*** **	**-0.131** *	**-0.181** **
	(0.0350)	**(0.0691)**	**(0.0776)**
Union	**0.412*** **	**0.128*** **	**0.126** **
	(0.0407)	**(0.0450)**	**(0.0564)**
Occupation			
Base: Manager			
Professional	-0.0177	-0.160	-0.157
	(0.0953)	(0.108)	(0.126)
Technician	-0.125	-0.163	-0.182
	(0.109)	(0.107)	(0.130)
Clerk	-0.0788	-0.143	-0.147
	(0.0876)	(0.123)	(0.149)
Service and Sales	**-0.522*** **	**-0.177** *	-0.173
	(0.0851)	**(0.0974)**	(0.127)
Agriculture	**-0.808*** **	**-0.559** *	**-0.612** *
	(0.164)	**(0.313)**	**(0.358)**
Artisan	**-0.495*** **	-0.167	**-0.315** **
	(0.0970)	(0.123)	**(0.154)**
Machine Operator	**-0.549*** **	-0.249	**-0.471** **
	(0.125)	(0.204)	**(0.226)**
Elementary	**-0.677*** **	**-0.235** **	**-0.324** **
	(0.0876)	**(0.104)**	**(0.129)**
Geography			
Base: Traditional			
Urban	**0.254*** **	0.00368	-0.130
	(0.0408)	(0.0670)	(0.115)
Farms	**0.139** **	0.114	0.176
	(0.0619)	(0.101)	(0.127)
Wave			
Base: 1			
2	**0.109** **	0.112	0.0806
	(0.0445)	(0.103)	(0.126)
3	**0.195*** **	0.0896	0.0735
	(0.0398)	(0.174)	(0.220)
4	**0.223*** **	0.101	0.0871
	(0.0365)	(0.263)	(0.322)

5	**0.224*****	0.0269	-0.00541
	(0.0371)	(0.347)	(0.428)
Constant	**5.490*****	**4.291*****	
	(0.358)	**(1.122)**	
Observations	6 084	4 623	1 798
Number of pid		2,464	
R-Squared	0.484	0.186	0.085

Standard errors in parentheses. *** p<0.01, **p<0.05, *p<0.1. Column (1) includes OLS results. Column (2) includes fixed effects results, and Column (3) includes first difference results. OLS regression is weighted using cross-section weights to account for complex survey design. Fixed effects and first difference regressions are weighted using panel weights, which account for attrition and complex survey design.

The regression results presented above tell a mixed story. Black South African women experience a motherhood wage penalty, but this penalty is not experienced equally for all women. The most important result is that the wage penalty is not the same for each additional child a woman has. Women with more children experience a significant, and substantially higher penalty, than women with fewer children. This is consistent with previous research which suggested that women who have many children may struggle to maintain a career while caring for children (Becker, 1980). Interestingly, the age of children is not as important in determining the effects of the penalty on women's earnings when using panel data analysis. However, in OLS analysis, having young children does reduce average earnings for mothers slightly more than having older children. This is consistent with the findings of Aguero et al., (2020). Further research could expand on this by including children's age as categorical, or even continuous variables, to better understand the relationship between mother's earnings and their children's ages, as well as including the gender of the child, as female children are more likely to be involved in household chores than male children (Aguero et al., 2020).

6. Conclusion

Despite advances in female employment and labour market participation since the end of apartheid in South Africa, women continue to reap fewer benefits from the labour market than men. High unemployment rates further penalize South African women.

In this study, I have looked at the relationship between fertility and employment in South Africa and shown that South Africa is an anomaly: despite consistently high unemployment, especially among young women, fertility in South Africa has declined, and fertility rates, adolescent fertility rates and the average age at which women first give birth in South Africa are similar to other developing countries. This is contrary to economic theory, which predicts that low economic opportunities (proxied by a high unemployment rate) are correlated with high fertility rates (Raymo and Shibata, 2017). Some explanations for the reduction in South African women's fertility could be declining marriage rates, climbing ages at which women first get married, and high contraceptive use (Garenne et al., 2001). However, further research, especially research aimed at establishing a causal link between fertility and economic opportunity in South Africa is needed to better understand this relationship.

I then went on to study the effects of motherhood on women's earnings. Many researchers have worried that mothers and non-mothers are different (for example, non-mothers have higher levels of ambition or tenacity), which cannot be easily accounted for in an OLS regression analysis (Budig and England, 2001). Following the work of previous researchers, I used panel data methods to control for any unobserved heterogeneity. I used both fixed effects, as well as first difference, and compared these panel data results to Ordinary Least Squares. I found that a motherhood wage penalty does exist in South Africa, but the extent and significance of this penalty fluctuates depending on the econometric approach. Using OLS and first differencing, for example, I found that having an additional child is statistically significant and negatively correlated with earnings. However, using fixed effects, the effect of children on earnings became statistically insignificant.

Importantly, I found that the wage penalty differs *between* mothers, depending on the number of children mothers already have. The motherhood wage penalty does not affect mothers equally: mothers with two or more children experience higher penalties than mothers with fewer children. I also found that having young children is negatively correlated with earnings, although this was only significant in the OLS regression results. Overall, the results suggest that women in South Africa experience a motherhood wage penalty, which is influenced by both the age of children, as well as the number of children a woman has. My OLS results are similar to those of Aguero et al (2020), who found that having an additional child reduced the average earnings of women by 4.5%, when controlling for personal characteristics.

Since most women become mothers at some point in their lives, mothers make up the majority of the female labour force. Thus, balancing family-work life is a reality for most women in South Africa (and around the world). Understanding – and solving – the motherhood wage penalty is not a fringe issue, but a real policy issue that affects millions of South African women, and negatively impacts their ability to contribute to the South African economy. Family-friendly policies such as subsidized childcare and flexible working options for parents have shown great success in increasing women's participation in the labour market in other economies. However, improving women's access to the labour market is only part of the solution. Policies are also needed to help women participating in the labour market to find meaningful employment. Were South Africa to implement similar policies, women would be better equipped to contribute meaningfully to the South African economy.

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8. Appendix

Table A1: CSM and TSM Sample Size

	All Individuals			African women		
	CSM	**TSM**	**Total**	**CSM**	**TSM**	**Total**
Wave 1	26 776	0	26 776	11 629	0	11 629
Wave 2	22 972	5 565	28 537	10 372	2 735	13 107
Wave 3	24 336	8 246	32 582	10 890	4 049	14 939
Wave 4	25 292	12 076	37 368	11 362	5 947	17 309
Wave 5	26 774	12 660	39 434	11 504	6 240	17 744

Data Source: NIDS Wave 1-5 Pooled Dataset. The increase in CSMs over time can be explained by two features of the data: firstly, any babies born to CSM mothers were automatically assigned CSM status (Brophy et al., 2018). Secondly, in Wave 5, due to low response rates from certain subsets of the population, a top-up sample of CSMs was included in the Wave 5 sample (Brophy et al., 2018).

Table A2: Key statistics for Panel weights[11]

		NIDS Panel Weights		
	W1-W2	**W1-W3**	**W1-W4**	**W1-W5**
Observations	21 116	21 394	20 778	19 302
Mean	923,19	2329,60	2485,39	2754,71
Median	558,99	1428,00	1535,88	1684,11
Min	53,89	125,64	139,37	158,14
Max	6213,92	15 820, 56	16 810,17	19 267,01
		IPW Panel Weights		
	W1-W2	**W1-W3**	**W1-W4**	**W1-W5**
Observations	20 959	21 340	20 764	19 289
Mean	2426,48	2390,81	2305,76	2114,93
Median	1347,09	1301,96	1269,34	1215,47
Min	127,69	106,41	100,64	115,90
Max	19 892,04	19 552,63	19 617,94	15 075,20
		IPW Panel Weights (T+1)		
	W1-W2	**W2-W3**	**W3-W4**	**W4-W5**
Observations	20 959	20 436	22 054	22 691
Mean	2426,48	2018,78	1865,07	1784,08
Median	1347,09	1141,83	1074,11	1048,91
Min	127,69	92,72	85,83	102,36
Max	19 892,04	15 652,87	15 177,75	12 274,24
		IPW Panel Weights (T+2)		
	W1-W3	**W2-W4**	**W3-W5**	
Observations	21 340	19 882	20 495	
Mean	2390,81	1939,71	1721,88	
Median	1301,96	1104,20	1024,75	
Min	106,41	85,01	100,97	
Max	19 552,63	15 692,98	11 520,01	

Data Source: NIDS Wave 1-5 Panel. NIDS Panel Weights refer to panel weights between Wave 1 and a subsequent wave created by NIDS. IPW panel weights refer to panel weights created using own calculations between Wave 1 and a subsequent wave. IPW panel weights (T+1) refer to panel weights created between Wave T and Wave (T+1). IPW panel weights 9T+2) refer to panel weights created between Wave T and Wave (T+2).

[11] In creating the IPW weights, I followed the same procedure as the NIDS team, as specified in Brophy et al., (2018). As expected then, the panel weights I create for waves 1-3, 1-4 and 1-5 are very similar to the publicly available weights created by the NIDS team for these sets of waves. However, the Wave 1 -2 NIDS Panel weights differ substantially from the IPW Panel weights I created. The mean of the publicly released weights is lower than the wave 1 cross sectional weights- which cannot be right given that they are supposed to correct for attrition by weighting up individuals who remained in the sample in wave 2. I thus use the W1 -W2 weights I have created rather than the ones in the public data.

The results of Table A2 show that, up until Wave 5, the means of the IPW weights I created, and the NIDS Panel weights are fairly similar. The difference in means between the weights I created, and the NIDS Panel weights could be because the NIDS team scaled their weights to add up to the estimated population in South Africa (Brophy et al., 2018).

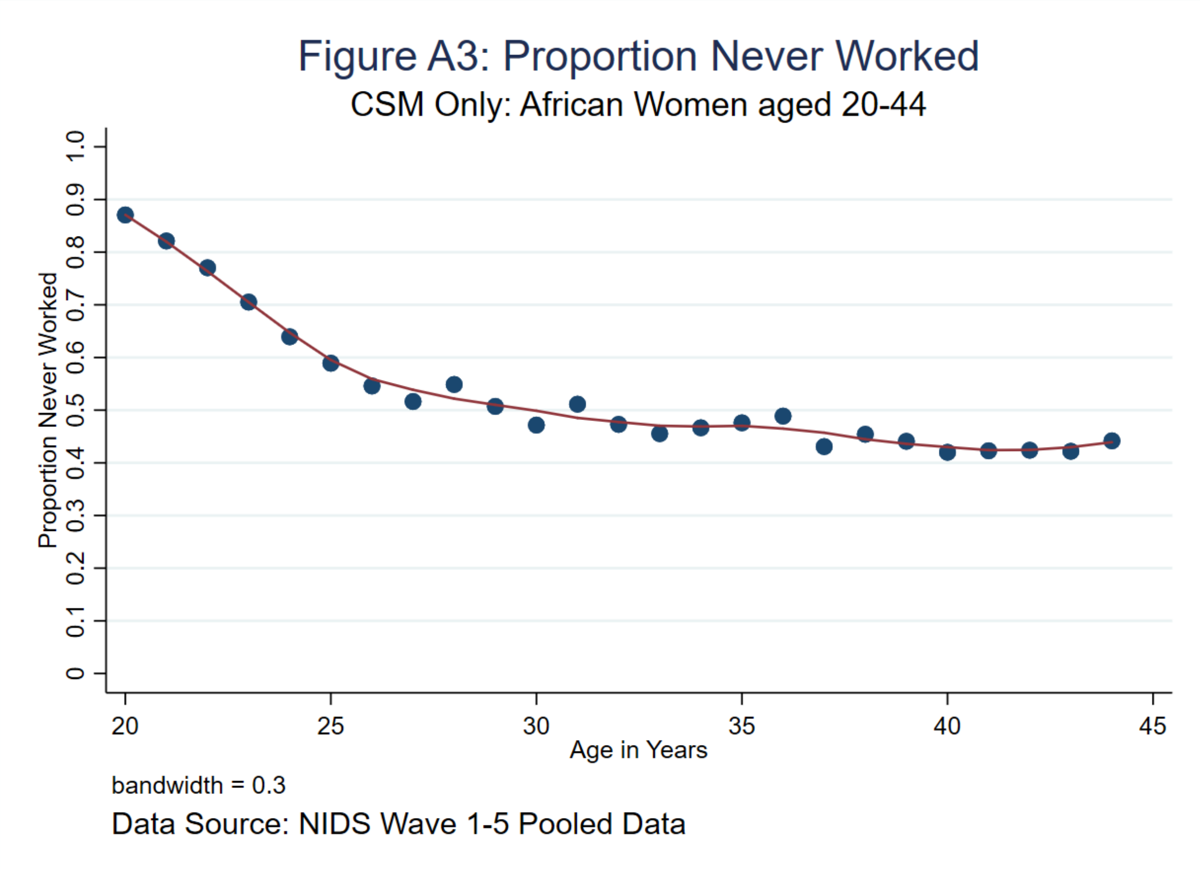

Table A4: Percentage of CSM mothers and non-mothers employed by age category

	Mother	Non-Mother	Total
20-24	8,33	38,28	12,60
25-29	22,03	31,15	23,33
30-34	26,46	17,18	25,14
35-39	23,53	9,72	21,56
40-44	19,65	3,67	17,37
Total	100	100	100
N	**5 776**	**801**	**6 577**

Data Source: NIDS Wave 1-5 Pooled Data. Data is weighted using calibrated cross-section weights which account for complex survey design. Sample includes only CSMs.

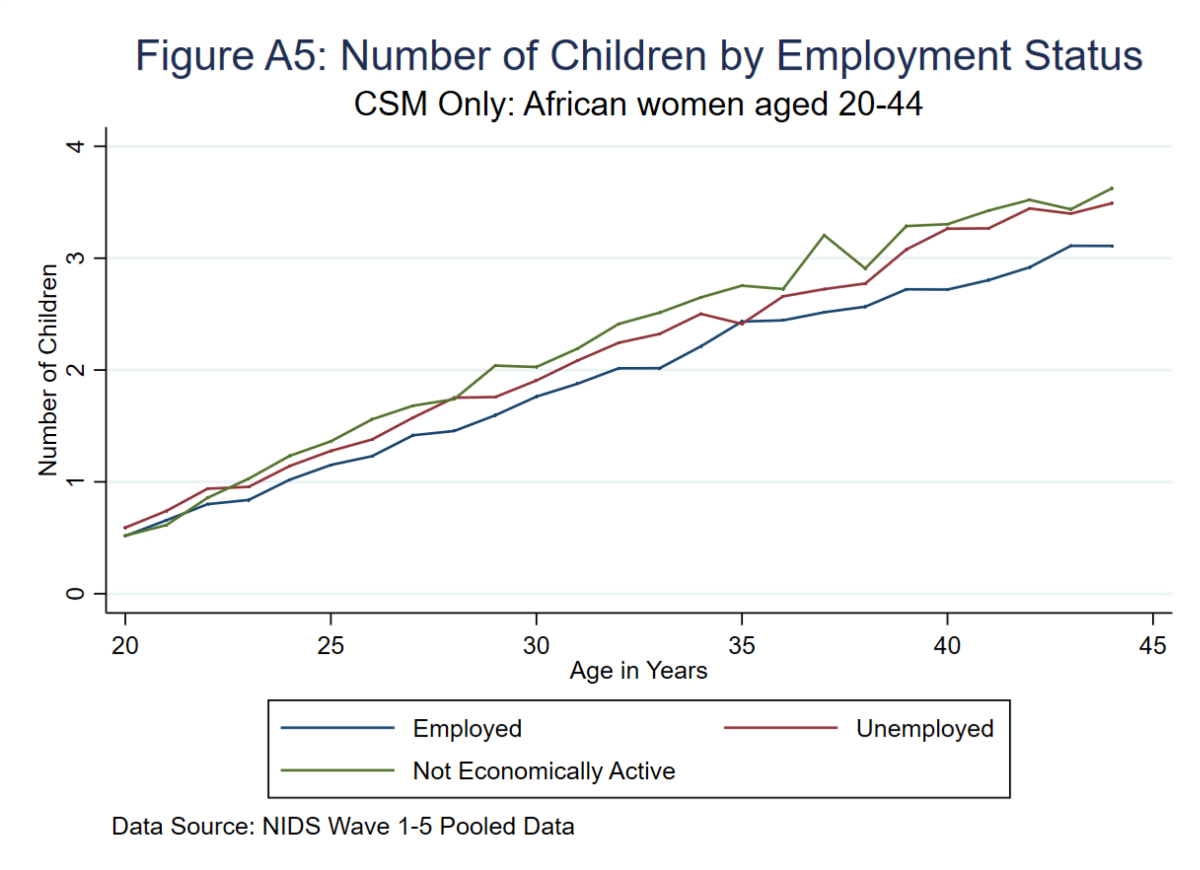

Table A6: Number of children for African women aged 20-44 by wave

		Wave					
		1	**2**	**3**	**4**	**5**	**T**
Number of Children	**0**	16,20	17,23	16,14	16,93	18,09	16,97
	1	26,74	29,18	29,94	30,95	30,78	29,65
	2	25,35	25,52	26,12	26,01	26,86	26,02
	3	14,56	14,37	14,98	14,59	14,37	14,57
	4+	17,16	13,70	12,82	11,51	9,91	12,80
	T	100	100	100	100	100	100
	N	**4 150**	**4 546**	**4 657**	**5 134**	**5 411**	**23 898**

Data Source: NIDS Wave 1-5 Pooled Data. Data is weighted using calibrated cross-section weights which account for complex survey design.

Table A7: Key Characteristics of CSM women aged 20-44 by Motherhood Status

VARIABLES		(5)	(6)	SE Difference between (5) and (6)	(7)	(8)	SE Difference between (7) and (8)
Monthly Take Home Pay (R)		5624,46	4516,59	**489,22 *****	4254,95	4870,91	**247,33 *****
Age (years)		27,43	33,43	**0,270 *****	31,31	36,37	**0,183*****
Number of children		-	2,28	**0,025 *****	2,37	2,16	**0,039*****
Categorical Children							
	1	-	31,67	**0,008 *****	29,05	35,32	**0,014*****
	2	-	33,67	**0,007 *****	34,08	33,1	**0,012*****
	3	-	19,56	**0,006 *****	19,55	19,57	**0,010*****
	4+	-	15,11	**0,007 *****	17,33	12,01	**0,007*****
Number of Non-biological Children		0,161	0,124	**0,192 *****	0,149	0,089	0,015
Marital status							
	Married	9,24	26,15	**0,012*****	24,26	28,78	0,012
	Living with Partner	3,23	9,98	**0,009*****	11,9	7,31	**0,008*****
	Widow	1,01	2,99	**0,004*****	1,59	4,94	**0,004*****
	Divorced	0,6	2,91	**0,003*****	1,44	4,95	**0,003*****
	Never Married	85,91	57,97	**0,020*****	60,81	54,02	0,015
Years of Education		11,61	10,69	**0,080*****	10,82	10,51	0,072
Part-time work		12,41	14,82	**0,067*****	15	14,56	0,007
Hours worked		39,56	39,22	0,831	39,36	39,03	0,731
Occupation							
	Manager	5,54	3,39	0,017	3,45	3,31	0,009
	Professional	18,65	15,02	0,025	13,21	17,49	0,018
	Technician	6,17	4,27	0,014	5,01	3,26	0,008
	Clerk	12,18	8,51	**0,019****	8,35	8,73	0,014
	Service and Sales	26,78	24,8	0,031	26,34	22,71	0,021
	Agriculture	0,02	0,36	**0,001*****	0,23	0,53	0,001
	Artisan	6,52	4,83	0,017	4,99	4,63	0,009
	Machine Operator	2,79	1,96	0,013	2,1	1,77	0,006
	Elementary	21,32	36,85	**0,026*****	36,33	37,56	0,023
Union Member		30,94	25,29	**0,028****	24,07	26,94	0,021
Geography							
	Traditional	19,61	28,01	**0,018*****	27,55	28,65	**0,012*****
	Urban	78,59	66,78	**0,018*****	67,59	65,64	**0,013*****
	Farm	1,8	5,21	**0,006*****	4,85	5,71	0,007
N		**801**	**5 899**		**3 489**	**2 410**	

Data Source: NIDS Wave 1-5 Pooled Data. Data is weighted using calibrated cross-section weights. Weighting accounts for complex sample design. Table includes only CSMs. Column (5) refers to childless women. Column (6) refers to all mothers. Column (7) refers to mothers with at least one young child (aged between 0-6 years old). Column (8) refers to mothers of only older children (aged between 7 -18 years old). Unless stated otherwise, all variables are in %. A woman is defined as a mother if she has given birth and at least one of her children is aged 18 or younger. *** p<0.01,

**p<0.05, *p<0.1.

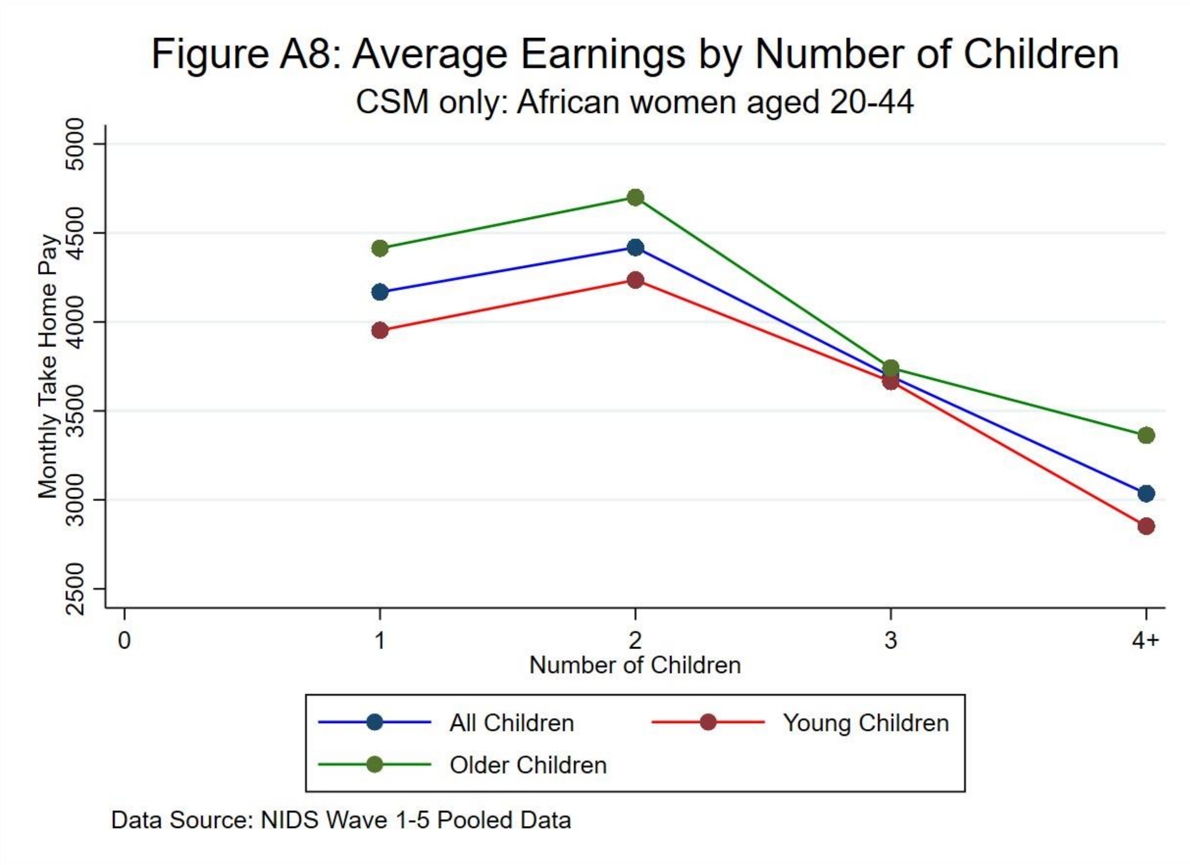

Figure A8: Average Earnings by Number of Children
CSM only: African women aged 20-44
Monthly Take Home Pay
2500
3000
3500
4000
4500
5000
0
1
2
3
4+
Number of Children
All Children
Young Children
Older Children
Data Source: NIDS Wave 1-5 Pooled Data

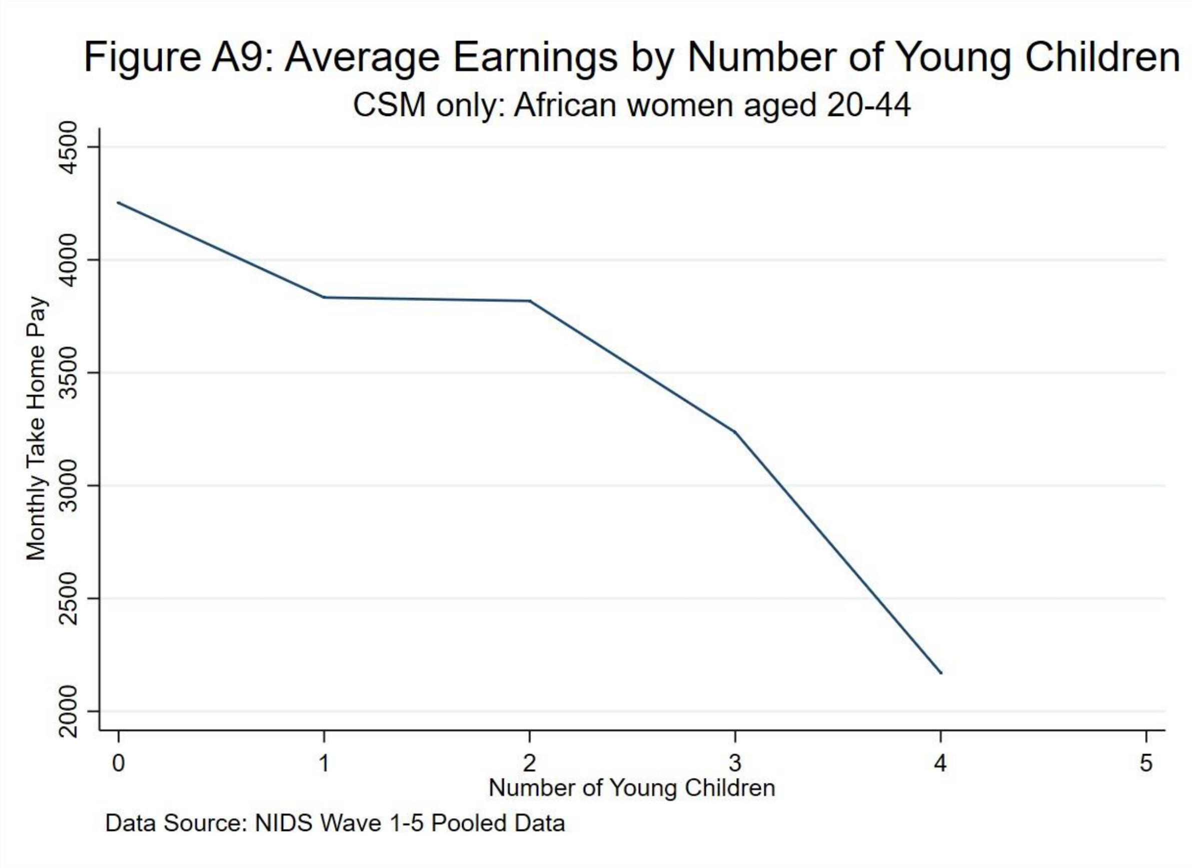

Figure A9: Average Earnings by Number of Young Children
CSM only: African women aged 20-44

Table A10: OLS Results for Motherhood Penalty including only CSMs

	(A1)	(A2)	(A3)
	Continuous Kids	**Categorical Kids**	**Young/Old Kids**
Number of Children	**-0.0433*** **		
	(0.0119)		
Categorical Children			
Base: 0			
1			**-0.130*****
			(0.0475)
2			**-0.122****
			(0.0492)
3			**-0.163*****
			(0.0572)
4+			**-0.247*****
			(0.0608)
Young Children		**-0.0541*****	
		(0.0193)	
Older Children		**-0.0355****	
		(0.0166)	
Non-Biological Children	**-0.0361****	**-0.0351***	**-0.0343***
	(0.0181)	**(0.0181)**	**(0.0182)**
Age	**0.0847*****	**0.0968*****	**0.0870*****

	(0.0234)	**(0.0236)**	**(0.0236)**
Age Squared	**-0.00114*** **	**-0.00137*** **	**-0.00118*** **
	(0.000347)	**(0.000352)**	**(0.000349)**
Education	**-0.0752*** **	**-0.0738*** **	**-0.0733*** **
	(0.0226)	**(0.0228)**	**(0.0228)**
Education Squared	**0.00937*** **	**0.00941*** **	**0.00930*** **
	(0.00146)	**(0.00147)**	**(0.00146)**
Hours worked	**0.170*** **	**0.169*** **	**0.170*** **
	(0.0260)	**(0.0258)**	**(0.0261)**
Marital Status			
Base: Married			
Living with Partner	**-0.143** **	**-0.143** **	**-0.140** **
	(0.0570)	**(0.0573)**	**(0.0565)**
Divorced	-0.00945	-0.0167	-0.0107
	(0.106)	(0.105)	(0.106)
Widowed	**0.188** **	**0.181** **	**0.187** **
	(0.0773)	**(0.0770)**	**(0.0772)**
Never Married	**-0.100*** **	**-0.0985*** **	**-0.0964** **
	(0.0374)	**(0.0374)**	**(0.0378)**
Union	**0.428*** **	**0.432*** **	**0.430*** **
	(0.0427)	**(0.0434)**	**(0.0432)**
Occupation			
Base: Manager			
Professional	-0.0632	-0.0637	-0.0649
	(0.114)	(0.115)	(0.114)
Technician	-0.195	-0.194	-0.201
	(0.125)	(0.125)	(0.125)
Clerk	-0.137	-0.136	-0.132
	(0.106)	(0.105)	(0.106)
Service and Sales	**-0.574*** **	**-0.573*** **	**-0.573*** **
	(0.104)	**(0.104)**	**(0.104)**
Agriculture	**-0.875*** **	**-0.875*** **	**-0.863*** **
	(0.193)	**(0.194)**	**(0.194)**
Artisan	**-0.531*** **	**-0.530*** **	**-0.530*** **
	(0.115)	**(0.115)**	**(0.114)**
Machine Operator	**-0.669*** **	**-0.670*** **	**-0.671*** **
	(0.135)	**(0.135)**	**(0.135)**
Elementary	**-0.726*** **	**-0.728*** **	**-0.727*** **
	(0.107)	**(0.106)**	**(0.106)**
Geography			
Base: Traditional			
Urban	**0.256*** **	**0.259*** **	**0.255*** **
	(0.0441)	**(0.0441)**	**(0.0439)**
Farms	**0.145** **	**0.141** **	**0.146** **
	(0.0637)	**(0.0656)**	**(0.0634)**
Wave			
Base: 1			
2	**0.106** **	**0.109** **	**0.105** **

		(0.0447)	**(0.0453)**	**(0.0452)**
	3	**0.189*****	**0.193*****	**0.188*****
		(0.0416)	**(0.0415)**	**(0.0419)**
	4	**0.224*****	**0.229*****	**0.223*****
		(0.0413)	**(0.0410)**	**(0.0414)**
	5	**0.225*****	**0.228*****	**0.226*****
		(0.0396)	**(0.0394)**	**(0.0397)**
Constant		**5.702*****	**5.527*****	**5.704*****
		(0.373)	**(0.386)**	**(0.373)**
Observations		4 705	4 705	4 705
R-Squared		0.490	0.490	0.491

OLS regression results above include only CSM women. Standard errors in parentheses. *** p<0.01, **p<0.05, *p<0.1. In Column (A1) the key independent variable is number of children. In Column (A2), the key independent variable is a categorical children variable, indicating whether a woman has given birth to 0, 1, 2, 3 or 4+ children. In Column (A3), they key independent variables are the number of young children (0–6-year-olds) and number of older children (7–18-year-olds) a woman has given birth to. Results are weighted using cross-section weights to account for complex survey design.

Table A11: Robustness Check for OLS Results in Table 17

	OLS
Number of Children	**-0.0658***** **(0.0156)**
Non-biological Children	-0.0248 (0.0242)
Age	**0.0749*** **(0.0420)**
Age Squared	**-0.000976** **(0.000640)**
Education	**-0.0993***** **(0.0271)**
Education Squared	**0.00983***** **(0.00191)**
Hours worked	**0.0997***** **(0.0349)**
Marital Status	
Base: Married	
Living with Partner	-0.100

	(0.0702)
Divorced	0.0636
	(0.172)
Widowed	**0.221***
	(0.115)
Never Married	**-0.103***
	(0.0562)
Union	**0.381*****
	(0.0516)
Occupation	
Base: Manager	
Professional	0.00809
	(0.155)
Technician	0.0166
	(0.182)
Clerk	-0.00507
	(0.153)
Service and Sales	**-0.475*****
	(0.148)
Agriculture	**-1.069*****
	(0.229)
Artisan	**-0.517*****
	(0.176)
Machine Operator	**-0.637*****
	(0.200)
Elementary	**-0.669*****
	(0.150)
Geography	
Base: Traditional	
Urban	**0.236*****
	(0.0529)
Farms	0.0969
	(0.0807)
Wave	
Base: 1	
2	**0.123****
	(0.0621)

	3	**0.226***** **(0.0583)**
	4	**0.266***** **(0.0580)**
	5	
Constant		**6.304***** **(0.686)**
Observations		2 491
Number of pid		
R-Squared		0.439

OLS regression results above include women employed in at least two waves of data. Standard errors in parentheses. *** p<0.01, **p<0.05, *p<0.1. In Column (A1) the key independent variable is number of children. In Column (A2), the key independent variable is a categorical children variable, indicating whether a woman has given birth to 0, 1, 2, 3 or 4+ children. In Column (A3), they key independent variables are the number of young children (0–6-year-olds) and number of older children (7–18-year-olds) a woman has given birth to. Results are weighted using cross-section weights to account for complex survey design.