Mind the gap: The distributional effects of COVID-19 on gender wage inequality in South Africa

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Abstract

At the end of March 2020, the South African government imposed a national lockdown to curb the spread of COVID-19, leading to substantial job losses in the context of already extreme levels of unemployment. However, less is known about the effects on job-retainers. This paper uses representative panel survey data to estimate the impact of the pandemic on the development of the gender wage gap across the entirety of the wage distribution in South Africa. Our Mincerian estimates suggest that the gender wage gap significantly increased by 37% at the mean, but this effect was heterogenous across the wage distribution. We show that gender wage inequality deepened most severely for those in the poorest 25% of the wage distribution, increasing at least 2.7 times more for these workers than the remainder of wage-earners. These results are robust to model specification, varying samples, and the use of monthly or hourly wages.

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1. Introduction

Wage inequality and discrimination on the basis of gender have been the subject of many empirical studies over the past few decades. Inequality in South Africa is already high, and progressive policies have been implemented by the state to address this. However, the onset of the coronavirus (COVID-19) pandemic and the subsequent national lockdown at the start of 2020 have had potentially devastating effects on inequality. In this paper, focus falls on the gendered impacts of the COVID-19 lockdown. Gender is an important factor in determining the economic impact of the pandemic. International literature suggests that, unlike previous recessions where men have borne the brunt of the economic downturn, this 'pandemic recession' is likely to disproportionately and persistently impact women (Alon et al., 2020). This is already clearly the case in South Africa, where initial research has shown that of the estimated three million fewer employed people in April relative to February 2020 as a result of the pandemic, two in every three were women (Casale and Posel, 2020; Ranchhod and Daniels, 2020).

However, although research has been conducted on the employment effects of the COVID-19 pandemic in South Africa, less research has been conducted on whether there have been inequality-deepening effects for those individuals who have managed to remain employed during the national lockdown. This paper aims to investigate the impact that the lockdown has had on gender wage inequality in South Africa for those individuals who have remained in employment during the period. Given international evidence that women have been found to take on greater shares of responsibility in the home relative to men during this period of working from home (Alon et al., 2020; Collins et al., 2020), it is our hypothesis that, even amongst those women who have remained employed, they are likely to have been more adversely affected by the onset of the COVID-19 pandemic relative to their male counterparts.

We make use of a comparable econometric specification using the first two waves of the National Income Dynamics Study: Coronavirus Rapid Mobile Survey (NIDS-CRAM) data, a broadly representative survey of adults in South Africa conducted from May to June and July to August 2020 respectively, to estimate the evolution of the unconditional and conditional gender wage gaps at the mean and across the wage distribution. We use these data as independent cross-sections as well as a balanced panel that are both broadly representative of the adult population and, in doing so, we construct estimates of the gender wage gap for a pre-lockdown period and compare them to estimates during the lockdown to determine whether there have been any inequality-deepening impacts of the pandemic on inter-gender wages. We begin by considering the unconditional and conditional gender wage gaps at the mean of the wage distribution through a descriptive and Mincerian earnings function analysis. We first show that women were 1.7 times more likely than men to experience employment loss, and that although this distribution of job loss was regressive irrespective of gender, lower-wage female workers were disproportionately affected: 60% of the poorest quintile of female workers lost employment on net, relative to 45% of their male counterparts. The increase in mean real wages for both genders highlights this differential selection into remaining employed. While the weekly working hour differential by gender did not vary significantly over time, the gender childcare gap increased by more than a factor of 3. We highlight a widening of the unconditional gender wage gap among middle-aged workers, workers of all education groups except tertiary-level, and technicians, associate professionals, and workers in elementary occupations. Our conditional Mincerian estimates suggest that the pandemic resulted in a 37% widening of the gender wage gap from February 2020 to over 51% in June 2020 – a statistically significant change. The magnitude of this change over time holds irrespective of whether hourly or monthly wages are used or whether the cross-sectional or panel samples are used.

To obtain a more nuanced understanding of the impact of the pandemic on gender wage inequality, we utilize Recentered Influence Functions (RIFs) to estimate the conditional gender wage gap at various points along the wage distribution in February and June 2020. We make use of three model specifications: namely, a pooled cross-sectional model; a reweighted model to account for structural labor market changes between periods; and a model estimated on a balanced panel of employed individuals. Our estimates indicate that the conditional gender wage gap is indeed heterogeneous across the wage distribution, and in particular, we find evidence of a widening monthly gender wage gap amongst the poorest 25% of earners as well as around the median of the earnings distribution. This result is robust to the specification of the model, as well as to whether we analyze monthly or hourly earnings. Simply put, we find that the poorest 25% of wage-earners were subject to deepening gender-wage inequality that was at least 2.7 times more severe for monthly wages, and at least 3.3 times more severe for hourly wages, than for the top 75% of wage-earners. Overall, these results are indicative of a trajectory of deepening gender inequality amongst an already vulnerable group of individuals.

Our estimates of the changes in the gender wage gap are fairly robust across model specifications that estimate the gap on samples that account for potential underlying changes in the characteristics of the sample under analysis. This result suggests that the widening of the gender wage gap (both amongst the poorest 25% of women and those at the median of the distribution) is not simply a function of a changing sample of employed individuals, but that there is potentially something else driving increases in gender wage inequality. Based on the international literature, possible drivers of this change could be that women are employed in jobs less amenable to remote working practices, or that women have disproportionately taken up the burden of childcare relative to men during the lockdown period (Alon et al., 2020; Collins et al., 2020). Through descriptive results, we find that there has indeed been an increase in the childcare gap between men and women during the lockdown period, suggesting that South African women's earnings are being negatively affected by the disproportionate childcare responsibility they faced during the national lockdown relative to men.

2. A brief overview of the South African lockdown

In response to the onset of the COVID-19 pandemic in South Africa, the government imposed a national lockdown beginning on 27 March 2020 to prepare the necessary health infrastructure as well as to delay and minimise the spread of the virus. The initial 'hard' lockdown was announced to last 3 weeks and was relatively stringent by international standards (Bhorat et al., 2020; Gustaffson, 2020), making no allowance for any non-essential activities outside the home. However, in the beginning of April 2020 this hard lockdown was extended for a further 2-week period, ending on 30 April 2020. During the initial 'hard' lockdown period, only those instrumental to the pandemic response were permitted to work. This group of workers included health workers; laboratory personnel; emergency personnel;

security services; essential workers for economic function (supermarkets, transportation, etc.); and those working in industries which could not economically shut down (for example, the mining and steel industries). Estimates using pre-crisis data suggest that just 40% of the employed were permitted to work under the most stringent level 5 (Francis et al., 2020). Köhler et al. (2021) highlight how the lockdown particularly jeopardized the livelihoods of those in the informal sector.

From May 2020, South Africa adopted a 5-level risk-adjusted lockdown strategy which implemented regulations according to the severity of the spread of COVID-19 in the country, which was still in place at the time of writing in 2021. From 1 May 2020, the lockdown regulations were relaxed slightly when the country moved to lockdown level 4 which mostly permitted a selected group of manufacturing plants to begin operating once more, but at reduced capacity. Between February 2020 and June 2020 – the period of analysis in this paper – South Africa's lockdown was adjusted from the initial level 5 lockdown to the more intermediate level 3 implemented on from 1 June 2020 that aimed to gradually open the economy and encourage economic activity once again. The level 3 regulations permitted almost all sectors to operate, except for the tourism and entertainment industries, whose activities were highly restricted or prohibited.

3. Literature review

3.1. The gender wage gap: local and global evidence

Gender wage inequality has been the focus of a large body of literature, both within South Africa and abroad. This research has been mostly unanimous in concluding that the gender wage gap, although narrowing, is still a persistent feature of the global labour market. According to Weichselbaumer and Winter-Ebmer (2005), early estimates of the gender wage gap in the international labour market began at approximately 65% in the 1960s and narrowed to approximately 30% by the late 1990s. Furthermore, in South Africa specifically, gender inequality and – in particular, the gender wage gap – has continued to narrow in the post-apartheid period (Mosomi, 2019; Posel and Casale, 2019). Mosomi (2019) estimated the South African gender wage gap at the mean of the wage distribution to have narrowed from approximately 40% in 1993 to approximately 16% in 2014. The gender wage gap at the median of the distribution has also decreased, but not to the same extent. In 1993, the gender wage gap at the median of the distribution was approximately 35%, while in 2015, it had decreased to approximately 23% (Mosomi, 2018). These estimates, using survey data, are slightly lower than those which use administrative data, where the gender wage gap is estimated to be approximately 35% in the South African formal sector. Estimates of the South African median gender wage gap are relatively comparable with international estimates for the same time period. In 2009, full-time female workers in the US earned approximately 80 cents per dollar earned by male workers, indicating a gender wage gap of approximately 20% (Hegewisch et al., 2010; Blau and Kahn, 2017). The German gender wage gap is at a comparable level, having been estimated to be approximately 20% (Antonczyk, Fitzenberger and Sommerfeld, 2010).

However, estimates of the gender wage gap at the mean or median of the distribution, while informative, can obscure important variation in wage inequality across the wage distribution. For example, Bhorat and Goga (2013) find that the gender wage gap is most pronounced (approximately 63%) at the 10th percentile of the distribution, but decreases to only approximately 7.2% by the 90th percentile. Although the reported size of the gender wage gap at different points along the South African wage distribution differs, the over-riding conclusion of heterogeneity in wage inequality across the wage distribution has been consistent. Ntuli (2007) shows that the gender wage gap has not consistently narrowed across the distribution. Rather, the narrowing of the mean gender wage gap was driven by decreasing inequality at the top and bottom of the distribution. Findings by Mosomi (2018) clearly support this narrative, showing stagnating inequality at the middle of the distribution with decreasing inequality at the top and bottom. This narrowing of the gender wage gap at the bottom of the distribution is likely driven by a combination of increased human capital characteristics and upward pressure on wages as a result of minimum wage legislation, particularly in the female-dominated domestic workers sector (Mosomi, 2018, 2019).

This heterogeneity of the gender wage gap across the wage distribution is not only a South African phenomenon, however. In the United States, Blau and Kahn (2017) find that the gender wage gap declined substantially more slowly at the top of the distribution than at the middle or bottom. As a result, the United States has experienced a widening of the gender wage gap at the top of the wage distribution. The German labour market has shown similar trends, with evidence of a shrinking gender wage gap only present at the bottom of the wage distribution, while wage inequality at the top has increased over time (Antonczyk, Fitzenberger and Sommerfeld, 2010).

Given that evidence presented in the literature provides a strong argument for heterogenous wage inequality across the wage distribution, we opt for a distributional analysis in this paper. By analyzing the gender wage gap across the entire distribution of wages, rather than simply at the mean, we will be able to better understand the interaction between wages and employment dynamics that have occurred in the South African economy due to the COVID-19 pandemic. This will provide a more nuanced platform from which to engage in policy discussions, as impacts on individuals at either end of the distribution will be hidden by simply estimating an average effect.

Studies on the gender wage gap, both locally and internationally, have provided a number of socio-economic characteristics that impact wage inequality. For example, the race of a worker has been found to be highly significant in correctly estimating the gender wage gap. Hinks (2002) found that the gender wage gap at the mean of the distribution is found to be highest amongst White individuals at approximately 40%, whilst amongst Coloured individuals, the gap is only estimated to be approximately 5%. Similarly, the age of workers is found to be a significant driver of the gender wage gap. Wage inequality between men and women is substantially lower for younger cohorts (Mosomi, 2019). The gender wage gap increases steadily over the course of an individual's lifetime; however, this is potentially explained by labour market interruptions as a result of childbirth for women (Budlender, 2019), or that women are more likely to be employed in occupations that provide limited room for real wage growth (Mosomi, 2019).

Education is a further factor that acts to narrow the gender wage gap, especially given the complementarities that arise between education and skills-biased technical change. Specifically, Mwabu and Schultz (2000) argue that the returns to higher education are higher for women. In recent years, women have realized greater increases in human capital than men, and there has been a pattern of skills-biased technical change underway in the South African economy (Mosomi, 2019). Combined, these factors are thought to explain why education has played a large role in the narrowing of the South African gender wage gap (Mosomi, 2019). Skills-biased technical change has not only narrowed the gender wage gap in South Africa, but all around the world. The mechanization of occupations that have a focus on manual or routine tasks has primarily occurred in male-dominated occupations, thus placing downward pressure of male wages and narrowing the gender wage gap in the United States (Yamaguchi, 2018). Evidence from Germany supports these findings, showing that the returns to labour market skills have risen over time (Antonczyk, Fitzenberger and Sommerfeld, 2010). Coupled with the fact that labour market skills that receive lowest returns are predominantly held my men, this could partially explain the narrowing of the gender wage gap in parts of the developed world (Yamaguchi, 2018).

Occupational segregation is a persistent cause of gender wage inequality, with female-dominated occupations generally presenting a higher gender wage gap than male-dominated occupations (Hegewisch et al., 2010; Hinks, 2002). In fact, according to a predictive model proposed by Hegewisch et al. (2010), a high-skilled occupation in the United States that is 100% female would pay approximately 46% less than one that is 100% male.[3] A similar finding is true for female-dominated industries when compared to male-dominated industries. There is a general decrease in the gender wage gap as the proportion of male employment in the industry increases (Landman and O'Clery, 2020; Hegewisch et al., 2010). This finding holds in the South African context, and it is hypothesized that the reason for this has to do with compliance with the Employment Equity Act (No. 55 of 1998). In particular, because of legislation that forces South African firms to representatively hire female employees, it is necessary to entice female workers to enter and remain in male-dominated industries. The easiest way to accomplish this is through higher wages. Through this mechanism, the gender wage

[3] The predicted wages for men and women in these hypothetical occupations are $1 555 and $840, respectively.

gap in male-dominated industries is forced downwards and wage inequality decreases Landman and O'Clery (2020).

3.2. Gender wage inequality and COVID-19

Evidence from the local and global literature has shown that the gender wage gap can be influenced by several socio-economic characteristics and trends. The COVID-19 pandemic has had a large impact on both the local and global economy, and studies have shown the disproportionate impact it has had on women in South Africa (Casale and Posel, 2020). As a result, it is likely that gender-based wage inequality will also be affected. Given that at the time of writing, much of the world is still struggling with the COVID-19 pandemic, this area of research is rather sparsely populated, particularly for the developing world.

The COVID-19 pandemic has produced an economic crisis quite different to any other in recent history, and as such, the effects of the pandemic on economic outcomes is not clear-cut. For example, Alon et al. (2020) report that the Global Financial Crisis of 2007/2008 disproportionately impacted male labour market outcomes, while the COVID-19 pandemic has quite clearly had a more severe impact on female labour market outcomes. One channel through which this disproportionate effect on women has been felt is working hours. In the United States, women with young children have reduced their working hours between four and five times more than fathers, leading to the gender gap in working hours growing by between 20 and 50% (Collins et al., 2020). The effects of these reductions in working hours may feed through to future labour market inequality as employers may choose to reward longer working hours with higher pay and, as a result, increase male wages disproportionately over female wages once again (Collins et al., 2020; Alon et al., 2020).

It is possible that inequality in labour market outcomes has been exacerbated by an inability to work effectively from home. In the United States, it was found that only 28% of men and 22% of women were employed in so-called tele-commutable occupations and able to work from home Alon et al. (2020). This discrepancy in working conditions may lead to disproportionate job or pay losses for women, as they cannot meet the same obligations as before the pandemic. A similar result in the United Kingdom showed that women made up a greater share of employment amongst those sectors that needed to shut down during COVID-19 lockdown, thus disproportionately impacting women's ability to work, and ultimately, their wages during the pandemic (Blundell et al., 2020).

In the South African context, it is clear that women are still feeling the brunt of the COVID-19 lockdown. South Africa's national lockdown was implemented from the end of March 2020. Of the estimated three million less people employed in April relative to February 2020, women accounted for approximately two in every three less people employed (Casale and Posel, 2020). Using pre-crisis data, only 13.8% of workers have been estimated to be able to work from home (Kerr and Thornton, 2020). Considering these individuals are concentrated at the top end of the wage distribution, it is likely that wage inequality in South Africa is likely to increase as a result of the lockdown. Furthermore, with South Africa's lockdown-related workplace restrictions considered amongst the most stringent in the world (Gustafsson, 2020), impacts on wage inequality are likely to be more severe in South Africa than other comparable countries.

Indeed, preliminary evidence from recent work using the NIDS-CRAM data in South Africa has shown that, compared to before the national lockdown, 80% of women and 65% of men indicated that they had spent more than 4 extra hours per day on childcare (Casale and Posel, 2020). Furthermore, as the lockdown progressed, the unconditional childcare gap between men and women increased from approximately 2.9 hours per day in April 2020 to approximately 3.3 hours per day in June (Casale and Posel, 2020). It is clear then that there has been a deepening of the childcare gap between men and women in South Africa, which could disproportionately impact on women's ability to work. These disproportionate changes in women's childcare burden relative to men's could lead to further inequalities persisting – in particular, the gender wage gap. If women's time has been disproportionately taken up by childcare responsibilities, then they will have to disproportionately decrease the number of hours they work in response, which may lead to a deepening of the gender wage gap in South Africa, in accordance with the hypotheses put forward by Alon et al. (2020) and Collins et al. (2020).

4. Data

4.1. The National Income Dynamics Study: Coronavirus Rapid Mobile Survey

This paper uses data from the first two waves of the National Income Dynamics Study: Coronavirus Rapid Mobile Survey (NIDS-CRAM), conducted from 7 May to 27 June and 13 July to 13 August 2020, respectively. The NIDS-CRAM is a representative, individual-level, panel survey of adults in South Africa, which has been repeated over several months as South Africa's national lockdown progresses. Conducted as a collaborative research project by several South African universities, the aim of the survey is to provide frequent, representative data on key socioeconomic outcomes in South Africa during the COVID-19 pandemic and national lockdown. The survey forms part of a broader study that aims to inform policymaking using rapid, reliable research in the context of the COVID-19 pandemic. The survey instrument includes a wide array of questions on income and employment, household welfare, and COVID-19-related knowledge and behaviour.

The NIDS-CRAM sample was drawn using a stratified sampling design from a sample frame which consists of individuals resident in South Africa aged 18 years or older at the time of fieldwork in April 2020 who were surveyed in Wave 5 of the National Income Dynamics Study (NIDS) conducted in 2017.[4] Approximately 7 000 adults were successfully interviewed in NIDS-CRAM Wave 1 and 5 700 in Wave 2, representing a 19% attrition rate. Discussed below, the sampling weights account for non-random attrition across the panel.

The NIDS-CRAM Wave 1 and 2 data include information on individuals' wages in February (pre-lockdown), April (one month into lockdown) and June 2020 (three months into lockdown). To estimate the gender wage gap during the national lockdown, we choose to use the June 2020 wage data in the NIDS-CRAM Wave 2 due to the absence of required covariates for the April 2020 period. The data allow us to control for wage variation induced by differences in marital status, main occupation, highest

[4] The NIDS is a nationally representative, panel, face-to-face, individual-level, household-based survey conducted approximately every two years between 2008 to 2017.

level of education, and number of children present in the household to name a few.[5] Considering our analysis focuses on heterogeneity in wages conditional on employment, we restrict our within-wave samples to working-age adults (18-64 years) who were employed at the time of the relevant reference period of their earnings (that is, February or June 2020).[6] Considering our use of survey data, we use the weight, cluster, and stratum variables provided in the data to adjust for the complex survey design and correctly estimate the parameters of interest as well as their standard errors. Because in survey data analyses standard errors are based on variation between Primary Sampling Units (PSUs), this adjustment also accounts for other sources of variation within PSUs and therefore accounts for the panel dimension of the data.

Although our analysis is primarily pooled cross-sectional, we additionally compare our estimates to those using a balanced panel sample of individuals employed in both February and June 2020. The inclusion of a set of estimates from the balanced panel provides estimates of the gender wage gap across a constant sample of individuals, thus rendering the estimates potentially more comparable than those obtained through pooled cross-sectional analysis. For more information on the NIDS-CRAM sampling design, the interested reader is referred to Ingle, Brophy and Daniels (2020).

4.2. Earnings in the NIDS-CRAM data: Adjusting for outliers and selection into bracket response

In the NIDS-CRAM, respondents were asked to report an actual monetary (Rand) amount after taking deductions into account. If they were not willing, they were asked to report which bracket their income lies in. Simply ignoring bracket responses incorrectly ignores responses that may come from the top end of the income distribution. For instance, in an analysis of South African household survey data, Wittenberg (2017) shows that individuals who do so tend to have higher incomes. Thus, any analysis which does not

[5] Due to data limitations, we are however unable to control for several unavailable variables, such as trade union membership.

[6] This lower age bound of 18 years, as opposed to the standard lower bound of the working-age population of 15 years, is used because younger individuals were not sampled in the NIDS-CRAM.

address these concerns beforehand may produce biased estimates. We adopt several statistical techniques to address these issues and adjust raw earnings in the NIDS-CRAM data.

First, outlier values are identified and coded as missing by using the "extreme studentized regression residuals" approach as advised by Wittenberg (2017).[7] Second, we address selection into responding with bracket information by constructing bracket weights, calculated as the inverse of the probability of an actual monetary (Rand) response in a particular bracket in a particular wave multiplied by the provided sampling weight for each individual. We opt for the reweighting procedure rather than the use of within-bracket imputation as imputation can produce artificial spikes in the data at the imputation values, which would affect the percentiles – an important aspect of our distributional analysis here. The outcome of our reweighting process is summarized by the unweighted and weighted (with sampling and bracket weights) wage distributions in Figure A1 in the Appendix. The observed differences between the sampling and bracket weighted distributions are attributable to the varied likelihoods of responding with an actual monetary (Rand) amount across the distribution (see Table A1). Unless indicated otherwise, all estimates for all periods are weighted using these computed bracket weights. Lastly, it is important to note that this reweighting approach does not do anything about those who refuse to answer or who otherwise have missing data – it only corrects for bracket responses.

After these adjustments, our final cross-sectional samples consists of 2 590 employed, working-age individuals with non-missing monthly wage data in February 2020 (78.1% of the working-age employed sample) and 1 735 in June 2020 (78.8% of the working-age employed sample). Our balanced panel sample of employed adults with non-missing wage data consists of 1 382 individuals. All wage data were inflated to April 2021 Rands (US$1 was approximately R14.90 at the time of writing). We

[7] This adjustment resulted in just three February 2020 earnings values being coded as missing in the NIDS-CRAM Wave 1 data, and two June 2020 earnings values in the NIDS-CRAM Wave 2 data.

focus on real monthly wages in our analysis while accounting for working hours in our regression models, but additionally report hourly wage estimates where relevant in the Appendix.[8]

5. Method

This section very briefly discusses the method used for estimating the unconditional and conditional gender wage gaps in this paper. Although there are a number of methods available, the choice of method was informed by a combination of the best practice in the available literature and practicality of implementation given the size of the sample in the first two waves of the NIDS-CRAM. First, we estimate the unconditional and conditional gender wage gaps separately for both February and June 2020 at the mean through Mincerian earnings regressions. That is, we employ Ordinary Least Squares (OLS) to regress the natural logarithm of real monthly wages on a vector of observable covariates, with the coefficient of interest being that of a binary indicator for women. Specifically, we estimate the following equation:

$$logw_i = \beta_0 + \beta_1 female_i + \beta_2 \boldsymbol{X}_i + \varepsilon_i \qquad (1)$$

where $logw_i$ is the natural logarithm of the real monthly wage of individual *I*; $female_i$ is a dummy variable equal to one if individual *i* is self-reported female and zero otherwise; $\boldsymbol{X}_i$ a vector of observable covariates including age, age squared, self-reported race, highest level of education, marital status, geographic area, province of residence, home language, number of household members younger than 18 years, a dummy variable for living with at least one child younger than 7 years, main occupation, and weekly working hours. Due to data limitations, we are unable to include two common variables in Mincerian equations in this vector: tenure and potential experience.[9] ε_i represents the error term. This allows us to estimate the evolution of the conditional gender wage gap at the mean; that is, the

[8] Respondents who were employed but report working zero hours per week are not of concern considering they only represented 4.4% of the February 2020 sample with non-missing wage data and 2.4% of the relevant June 2020 sample.

[9] Data on tenure is not included in the NIDS-CRAM and moreover cannot be proxied as a function of when respondents started and ended school given the additional absence of this data. Potential experience is commonly generated as a function of age and years of schooling. Although the NIDS-CRAM includes data on age and highest level of education, detailed data on the latter is only included up to the end of the secondary level. For tertiary-level education, the survey only has binary data on whether or not a respondent has *any* completed tertiary-level qualification. This prohibits us from generating potential experience for approximately a third of the sample.

percentage difference between real monthly wages of men and women on average in February versus June, while accounting for variation in wages induced by variation in other characteristics. Our estimate of interest is, of course, β_1: the coefficient on the binary indicator for women.

After estimating the conditional gender wage gaps at the mean of the wage distributions in February and June 2020, we seek to analyse the gap across the entire distribution in both periods. The econometric method utilised in this paper for this purpose is that of Recentred Influence Function (RIF) regressions, as proposed by Firpo, Fortin and Lemieux (2009). The RIF regression method essentially allows for the marginal effect of a change in an explanatory variable on the dependent variable to be estimated at each of a number of specified quantiles of the unconditional distribution of the dependent variable (Firpo, Fortin and Lemieux, 2009). In other words, the coefficients from a RIF regression at the τ^{th} quantile can be interpreted as the marginal effect of a change in x_i on y at quantile τ. Estimation of a RIF regression relies heavily on the influence function, defined as $IF(Y; v, F_Y)$, where Y is the dependent variable of interest; v is the distributional statistic of interest in the influence function – in this case, the quantile; and F_Y is the unconditional distribution of Y. To produce a recentred influence function, one simply adds the influence function to the distributional statistic of interest. In other words, given that the functional form of the quantile influence function is known, the recentred influence function for the τ^{th} quantile of the distribution, q_τ, is defined as follows:

$$RIF(Y; q_\tau, F_Y) = q_\tau + \frac{\tau - \mathbb{I}[Y \leq q_\tau]}{f_Y(q_\tau)} \tag{2}$$

The regression estimation simply uses this newly defined RIF of Y_i, estimated at quantile q_τ as the dependent variable in an OLS regression. This leads to a regression model of the following form to be estimated:

$$RIF(Y; q_\tau, F_Y) = \alpha_\tau + \beta_\tau female_i + \gamma_\tau X_i + \varepsilon_i \tag{3}$$

In the above model, the dependent variable is the log of monthly wages[10]; the matrix of individual-level

[10] Although the log of monthly wages is the preferred dependent variable for this research, we also examine the log of hourly wages. This is in part a robustness check of our main results due to concerns that using monthly wages will overestimate the size of the gender wage gap (Bhorat and Goga, 2013; Weichselbaumer and Winter-Ebmer, 2005).

covariates, X_i, includes variables such as race, marital status, home language, occupation and education level, amongst others. The coefficient β_τ is the point estimate of the gender wage gap at the τ^{th} quantile, which is the estimate of primary interest to this study.

One particular concern regarding the estimation of the gender wage gap is concerns around endogeneity of estimates due to the selection of individuals into labor force participation. Mwabu and Schultz (2000) find that women are significantly less likely to participate in the labor market than men, which introduces selection bias into the estimation of the gender wage gap. A number of studies have attempted to correct for this bias by estimating a two-stage Heckman selection model and controlling for the inverse Mills ratio in their subsequent regression estimates (Ntuli, 2007; Hinks, 2002; Mwabu and Schultz, 2000). However, in all these cases, the coefficient on the selection term remained insignificant, indicating that controlling for sample selection did not substantially improve the estimates produced.

Even though studies have found selection effects to be insignificant, we suspect that this is unlikely to be the case here. As a result of the national lockdown, many individuals lost their jobs, however, these job-losers were not a random sample of the employed; rather, those individuals who lost their jobs were disproportionately concentrated amongst the more vulnerable and lower-earning groups in South Africa (Ranchhod and Daniels, 2020; Casale and Posel, 2020). As a result, it is important to account for the changes in the characteristics of the employed population between February 2020 and June 2020.

In the absence of a valid instrument to control for selection in a Heckman two-stage model, we opt to make use of the DiNardo, Fortin and Lemieux (hereafter DFL) reweighting technique to create a hypothetical distribution for June 2020 wage earners that matches the distribution of characteristics in the February 2020 wage-earner population (DiNardo, Fortin and Lemieux, 1996). This technique has been used previously with the NIDS-CRAM data to investigate poverty incidence by Jain et al. (2020). The DFL reweighting procedure essentially entails adjusting sample weights for June 2020 by a factor θ, defined as follows:

$$\theta = \frac{\Pr(T = Feb|X)\Pr(T = June)}{\Pr(T = June|X)\Pr(T = Feb)} \tag{4}$$

These components are relatively simple to estimate from the data: the unconditional probabilities are simply the probability of an observation in the pooled sample being from February 2020 or June 2020, while the conditional probabilities are estimated from a binary choice model with a dependent variable equal to 1 if the observation is from February 2020, and 0 if it is from June 2020. The covariates in X capture characteristics of the total group of wage earners that we expect may differ between the two periods, such as race, gender, occupation, child cohabitation status, and others.

Figure A2 in the Appendix plots the wage distributions for February 2020, June 2020, and the reweighted June 2020 sample that has the same characteristics as the February 2020 sample. The hypothetical June distribution lies noticeably to the right of the real June distribution, indicating that there has been a selection effect at play to arrive at the June 2020 sample. As a result, the use of the DFL reweighting technique to control for selection is justified in this case. In essence, the DFL reweighting procedure is equivalent to an inverse probability weighting (IPW) procedure, which is commonly used to weight regression analysis in the programme evaluation literature (Elder, Goddeeris and Haider, 2015). To this end, we rerun the June 2020 regressions as specified in Equation (3), above, but using the adjusted DFL weights as regression weights.

As mentioned above, this reweighting procedure aims to correct for sample biases that arise due to differences between the February 2020 and June 2020 sample of wage-earners. Estimating the gender wage gap on the panel of wage-earners employed in both periods serves as a second possible method of ensuring comparable samples between the two periods of interest. As a result, we present estimates for three distinct models in this paper: first, the estimates obtained through pooled cross-sectional analysis; second, the estimates obtained from the DFL reweighting technique; and third, the estimates obtained from the balanced panel of wage-earners.

6. Descriptive statistics

Considering the intra-gender wage distributions, we observe notable shifts for both men and women from before to during the lockdown in South Africa. Figure 1 presents the real monthly wage distributions for men and women in February and June 2020. For men, the distributions suggest that the increase in wages was driven by a reduction in the number of poorer earners towards the bottom of the distribution and an increase in the number of richer earners from the middle towards the top. This is indicative of higher earners being more likely to remain employed during the lockdown period. For women on the other hand, the increase in wages seems to be driven also by a reduction in the number of poorer earners but also an increase in the number of earners in the middle of the distribution – again indicative of selection of higher-wage earners into remaining employed. Through two-sample Kolmogorov-Smirnov (KS) equality-of-distributions tests, we find all of these distributional shifts – both within-wave across-genders and within-gender across-waves – are statistically significant at the 1% level.

[INSERT FIGURE 1 HERE]

Changes in the gender wage gap may be attributable to not only changes in wages but several other mechanisms in the context of the pandemic, including differential inter-gender changes in employment, working hours, and childcare hours. Table 1 presents descriptive statistics of these outcomes for men and women in South Africa from before to during the lockdown. We observe that although higher-wage men and women were more likely to remain employed, women in general were more likely than men to experience employment loss, particularly low-wage-earning women, and the childcare gap between men and women increased through both an increase in childcare for women but mostly through a significant decrease for men. Comparing the cross-sectional samples in panel (a), employment among women decreased by nearly 20%, but just 12% among men, increasing the gender employment gap by 33% – a statistically significant difference. Mean monthly wages increased for both men and women at similar rates, likely attributable to selection into remaining employed for higher-wage workers (explored in more detail in Figure 2), resulting in the unconditional gender wage gap at the mean remaining constant, with women earning approximately 59% of men's earnings in both February and

June 2020.[11] Similarly, mean weekly working hours increased for both men and women, with no significant changes in the inter-gender gap. On the other hand, regarding childcare,[12] women pre-lockdown on average spent 1.7 more hours per day than men looking after their children – a statistically significant difference. During the lockdown, this childcare gap more than trebled to 5.3 daily hours, partially through a 6% increase of mean childcare hours among women but primarily through a 31% reduction among men.

These results hold when the sample is restricted to the panel sample of workers who remained employed over the period. Although workers in this sample expectedly earn higher wages as indicated in the table, this suggests that these changes over time are not biased by the underlying differences in characteristics between the February and June samples.

[INSERT TABLE 1 HERE]

As discussed above, the observed increase in real monthly wages on average among both men and women is driven by lower-wage workers being more likely to experience employment loss relative to their higher-wage counterparts. Ranchhod and Daniels (2021), using the same data but comparing changes between February and April 2020, also highlight this compositional shift. However, we highlight here that low-wage-earning women were worse affected relative to their higher-wage earning or male counterparts. Figure 2 presents our estimates on net employment changes over the period by gender across the pre-pandemic (February 2020) wage distribution. Although all groups experienced

[11] This, in turn, is indicative of a 41% gender wage gap.

[12] The NIDS-CRAM does not contain any data on childcare hours for any period prior to April 2020. To construct a pre-pandemic estimate for February 2020, we make use of data from two items from the Wave 2 questionnaire and compare it to April 2020 responses for daily childcare hours: (1) "*In April, did you personally spent more time than usual looking after children?*" and (2) "*How much more time did you spend per day?*". The following categorical responses were available for the latter item: (i) 'Nearly one hour more', (ii) '1-2 hours more', (iii) '3-4 hours more', and (iv) 'Over 4 hours more'. To construct a conservative pre-pandemic estimate, we assume (i) was equivalent to the same amount of time, (ii) 1 hour more, (iii) 3 hours more, and (iv) 4 hours more.

employment losses, the poorest 20% of female workers experienced a net employment reduction of close to 60% (922 000 workers) over the period, in contrast to the poorest 20% of male workers where the relevant rate is equivalent to 45% (619 000 workers). In other words, just 20% of female workers accounts for more than 42% of all jobs lost among women over the period. Both these within-gender and between-gender differences over time are statistically significant.

[INSERT FIGURE 2 HERE]

The above dynamics in gender wage inequality are enlightening but, in aggregate form, mask substantial underlying between-group variation. Table 2 presents the mean real monthly wages by gender across several groups of workers in February and June 2020 as well as the computed intra-group unconditional wage gaps; that is, the ratio of the average women's wage relative to that of men's in a given month. We investigate these gaps between several groups by age, highest level of education, and main occupation to name a few. Overall on aggregate, as noted above, the unconditional gender wage gap at the mean remained relatively constant at 41% over the period (equivalently, women's wages are 59% of men's wages), although the gap is still evident and statistically significant in both periods. By age, middle-aged workers aged 35 – 49 years exhibited the largest gaps in both periods and slightly widened over the period to 52%. Whereas the gap remained constant for young workers, it significantly narrowed for older workers from 45% to 5%, although these gaps are not statistically significant due to the small sample size of this group. By self-reported race, we only observe statistically significant gaps for the Black African and White groups of similar magnitudes (44%) in February 2020.[13] Over time, the gap evident among White workers narrowed to 35%, primarily driven by a reduction in the mean wage of male workers in this group, whereas the gap among Black African workers remained relatively constant.

[13] The absence of statistically significant gender wage gaps for other self-reported race groups is likely attributable to the small sample sizes of these groups in both periods.

[INSERT TABLE 2 HERE]

Notably, by highest level of education, all groups experienced an increase in gender wage inequality except for tertiary-level educated workers among whom inequality decreased. Notably, we observe a significant and steep, negative gender wage gap gradient in February, but a positive and steeper gap in June 2020. Prior to the lockdown, tertiary-level educated workers exhibited the largest gap of 50% and workers with up to a primary-level education exhibited the smallest gap of 33%. On the other hand, during the lockdown in June 2020 these roles reversed: tertiary-level educated workers exhibited the smallest gap of 37% and workers with up to a primary-level education exhibited the largest gap of 62% – a significant increase of 43% – primarily due to an increase in the mean wage among men in this group. By occupation, we find that nearly half of all workers (46% and 43% in February and June respectively) experience narrowing gaps. These include managers, service and sales workers, skilled agricultural workers, craft and related trades workers, and plant and machine operators. On the other hand, technicians and associate professionals and workers in elementary occupations experienced a widening of the gap, representing 29% and 27% of workers in February and June, respectively. Finally, across the wage distribution, we only find evidence of a significant gap among the richest 20% of workers of 28% prior to the lockdown, which narrowed slightly to 21% in June 2020. For the remainder of the distribution, most estimates of the gap are close to and are not statistically significantly different from zero.

It should however be noted that all these gender wage gap estimates are endogenous and do not account for characteristic differences both between and within groups over time. Of course, the observed variation in inter-gender wages can be explained by factors other than gender itself. We account for the variation in wages attributable to these characteristics in our multivariate modelling to follow.

7. Model results

We now turn to examining changes in the gender wage gap while controlling for possible confounding variables. First, we conduct this analysis at the mean of the distribution; that is, we estimate a Mincerian earnings function using OLS as per specification (1) for February and June 2020 separately, allowing us to estimate the evolution of the conditional gender wage gap at the mean; that is, the percentage difference between the real monthly wages of men and women on average, while accounting for variation in wages induced by variation in other characteristics. The succinct results of these regressions are presented in Table 3, while the complete results are available in Table A2 in the Appendix. We also report the equivalent estimates using hourly as opposed to monthly wages in Table A3.

[INSERT TABLE 3 HERE]

Overall, our estimates suggest that even after controlling for differences in several individual-level characteristics between men and women, both the unconditional and conditional monthly gender wage gaps were higher during lockdown in June 2020 relative to before in February 2020 – at least on average. Without controlling for any confounders, the average woman earned 37.1% less wages than men in February 2020 but nearly 59.5% less in June 2020 – indicative of an increase in the unconditional gap of about 60%. These differences in estimates are statistically significant at the 1% level. This widening of the gap is smaller but still significant after we control for the aforementioned vector of covariates, from 37.4% in February 2020 to 51.2% in June 2020 – indicative of an increase in the conditional gender wage gap of about 37%. These estimates are also more precisely estimated as indicated by the smaller standard errors. The equivalent hourly wage estimates in Table A3 are similar in magnitude both in a given period and the change over time. When we restrict the sample to those who remained employed over the period, the magnitudes of the gaps – irrespective of if monthly or hourly wages are used – are slightly smaller in all periods, but the magnitude of the change over time is not statistically dissimilar from that when using the cross-sectional samples, again suggesting the widening of the gender wage gap at the mean is not biased by the underlying differences in characteristics between the February and June samples.

Next, we explore the evolution of the conditional gender wage gap across the entire earnings distribution, as opposed to just at the mean. One particular concern with the results presented in the remainder of this section is that in order for the wage regressions to be comparable between the two periods, we cannot control for industry.[14] Research has shown strong results supporting the fact that an individual's industry of employment can have an impact on the size of the gender wage gap (Landman and O'Clery, 2020). In particular, the gender wage gap is found to be lower in male-dominated industries, likely due to male-dominated industries needing to diversify their workforce and recruit and retain female employees (Landman and O'Clery, 2020). In order to check the extent to which industry impacts our results, we ran the June 2020 regressions including industry dummies (as this data was available in the NIDS-CRAM Wave 2 data). The resulting estimates are very comparable to those presented below, and as a result, we are confident that the results below do not suffer greatly from not having industry included as a control.

Table 4, below, presents estimates for the gender wage gap in February and June 2020 across the monthly wage distribution for our three models of interest: namely, the pooled cross-sectional model; the reweighted model; and the panel model. Two clear results emerge across all three models: First, the gender wage gap is present and statistically significant across the majority of the wage distribution in both periods. Second, across all three models, there seems to be a clear deepening of the gender wage gap between February and June, particularly for those workers at the bottom of the wage distribution.

[INSERT Table 4 HERE]

The results in Table 4 indicate that the gender wage gap is indeed heterogenous across the wage distribution, with point estimates of the gap in February ranging from as low as 4% for the 10th percentile, to 72% at the 75th percentile. Estimates of the gap for the balanced panel sample have a smaller range – between 18% and 57% – but generally seem to follow the same broad trends as the estimates from the other two models. As a sense check, we note that our estimates of the gender wage gap in the pre-pandemic period accord with those presented by Mosomi (2018) and Bezuidenhout et al.

[14] This is due to the fact that industry data is not captured in the NIDS-CRAM Wave 1 survey for February 2020.

(2019). These researchers estimate a gender wage gap of approximately 35% at the median of the wage distribution, and our estimates are broadly in line with this figure. Although our estimate at the median of the distribution is between 22% and 28%, depending on the sample used, the 95% confidence interval for these estimates overlap with reported figures in the literature, indicating a comparable result.

Furthermore, all three presented models show a sharp increase in the estimated gender wage gap in June 2020, particularly at the bottom of the wage distribution. In June 2020, estimates of the gender wage gap range between a low of 26% and a high of 77%, indicating a substantial upward tick in gender wage inequality following the implementation of the national lockdown. Here, however, the concern lies in the fact that the largest increases in the gender wage gap seem to be clustered amongst those at the bottom of the wage distribution, and this finding is robust no matter the model under consideration.

When plotting the extent of the changes in the gender wage gap between February and June 2020, we see that the overall pattern of changes in gender wage inequality has an approximate inverse-U shape (see Figure 3, below). While not shown on the graph, we note that the only statistically significant changes in the gap are found at or below the 25th percentile of the wage distribution, or around the median. We do, however, report these point estimates of the change as well as the statistical significance in the appendix (see Table A4).

Even though there are two tranches of estimates that show statistical significance, we note that proportionally speaking, the bottom of the wage distribution saw a much larger increase in gender wage inequality. Estimates of the increase in the gender wage gap below the 25th percentile have increased by between 114% and 447% on average – model dependant – while the remainder of the distribution has only seen an increase of between 19% and 42% in the February estimates of the gap.[15] This is indicative of the bottom 25% of the distribution experiencing a disproportionate increase in gender

[15] Note that point estimates at the median of the distribution have increased by approximately 75% on average.

wage inequality, and our estimates indicate the poorest quarter of the wage distribution was hit *at least* 2.7 times harder than the remainder of the distribution on average.[16]

[INSERT Figure 3 HERE]

These results are particularly striking as they indicate that the bulk of gender wage inequality increases was focused amongst already-vulnerable individuals. A similar result emerges when considering hourly wage gaps: Here, the proportional increase in the gap for the bottom 25% of the wage distribution lies between 90% and 582%, depending on the chosen model, while for the remainder of the distribution increases in the gap are between 15% and 27% (see Table A5 and Figure A2: Difference in hourly gender wage gap estimates between February and June 2020 in the appendix for these hourly estimates). These findings indicate that the poorest quarter of wage earners were hit *at least* 3.3 times as hard as those above the 25th percentile of the wage distribution. All this is to show that our conclusions are relatively robust to which definition of wages are used to define the gender wage gap, as well as the choice of model specification (pooled cross-sectional, reweighted, or panel).

We further note that the estimates of the change in the gender wage gap are fairly robust to model specification: all three lines in the above figure are fairly closely clustered across the entirety of the distribution, indicating that estimates of the change in the gender wage gap are not drastically impacted by the changes in our sample. This would suggest that the deepening of the gender wage gap is not simply to do with structural changes in the labour market, such as the disproportionate employment loss suffered by women as a result of the South African national lockdown. Rather, these results imply that there were likely other factors at play, unrelated to the structural changes in the employed population, that led to these changes in gender wage inequality.

[16] At worst, our models indicate that the poor could have seen an almost 24.6 times greater increase in gender wage inequality than those above the 25th percentile of the wage distribution, however this estimate is obtained from the pooled cross-sectional sample that does not account for structural changes in the underlying sample between periods. The reweighting estimate indicates a 13.8 times more severe impact for the poorest quarter of wage-earners.

8. Conclusion and discussion

Unlike previous recessions where it has been observed that men have borne the brunt of the economic downturn, the COVID-19 ‘pandemic recession’ is likely to disproportionately and persistently impact women. In the context of South Africa, initial research has shown that of the estimated three million fewer employed people in April relative to February 2020, two in every three were women. However, less is known about the implications of the pandemic on those women who managed to remain in employment during the lockdown period. In this light, we use newly-available representative survey data to analyse the evolution of gender wage inequality in South Africa prior to and during the national lockdown. We do so by constructing estimates of the unconditional and conditional gender wage gaps through Mincerian earnings regressions and Recentered Influence Functions (RIFs) for a pre-lockdown period and compare them to similar estimates from during the lockdown to determine whether there have been any inequality-deepening impacts of the pandemic on inter-gender wages. Additionally, we analyse variation in gender wage inequality across the entire wage distribution, given the evidence of distributional heterogeneity in the South African literature. By making use of both the DiNardo, Fortin and Lemieux (DFL) reweighting technique, as well as analysis on a balanced panel of job-retainers, we confirm that out results are robust to sample selection concerns, considering the systematic differences between job-losers and job-retainers in the February and June 2020 samples.

We first show that women were 1.7 times more likely than men to experience employment loss, and that although this distribution of job loss was regressive irrespective of gender, lower-wage female workers were disproportionately affected with 60% of the poorest quintile of female workers losing employment. While the weekly working hour differential by gender did not vary significantly over time, the gender childcare gap increased by more than a factor of 3. We highlight a widening of the unconditional gender wage gap for several demographic groups of workers. Our conditional Mincerian estimates suggest that the pandemic resulted in a 37% widening of the gender wage gap from February 2020 to over 51% in June 2020 – a statistically significant change. The magnitude of this change over time holds irrespective of whether hourly or monthly wages are used or when the cross-sectional or panel samples are used.

When we further investigate this gap across the wage distribution, it is clear that the gap exists across the entire distribution but varies considerably. For most of the distribution, our distributional estimates of the gap in June 2020 are statistically insignificantly different from those in February 2020. However, we observe a significant widening of the gap amongst the poorest 25% of earners, as well as around the median of the distribution. The magnitude of the gender wage gap increase is proportionally much larger for those in the bottom quarter of the distribution, with these individuals being impacted at least 2.7 times more severely than those individuals in the top 75% of the earnings distribution. This finding is a concern for policymakers, considering that it speaks to deepening inequality amongst an already vulnerable group. A comparison of the relevant monthly and hourly wage gap estimates shows similar results, implying that the findings presented are robust to the choice of earnings variable.

The robustness of the results across model specification type for both hourly and monthly wages suggests that the changes in gender wage inequality are likely driven by something other than underlying structural changes in the sample of employed individuals between periods. International literature suggests that gender wage inequality could increase due to women being employed in jobs less amenable to remote working practices, or women who have disproportionately taken up the burden of childcare relative to men during the lockdown period (Alon et al., 2020; Collins et al., 2020).

While data limitations preclude us from investigating the ability of women's jobs to be performed remotely relative to men's, we can briefly examine average trends in childcare hours between genders. Aggregate trends in childcare time for South African men and women during lockdown indicate a 31% decline in childcare hours for men, while women's childcare hours increased by 6% relative to the pre-lockdown period. This disproportionate change in women's childcare responsibility could potentially then be a factor influencing women's earning ability, and thus, leading to increases in gender wage inequality.

From a policy perspective, interventions which aim to provide income support to women at the bottom of the wage distribution would be particularly effective in alleviating gender wage inequality. Considering South Africa has a relatively comprehensive and progressive social assistance system benefiting over one in every three individuals in the country (Köhler and Bhorat, 2021), one potential intervention is to target female earners through intensive margin increases, such as a cash transfer top-up. South Africa's largest cash transfer in terms of the number of beneficiaries – the Child Support Grant (CSG) – is not only pro-poor, but nearly all (approximately 98%) caregivers who receive the grant on behalf of eligible children are women. Depending on the trajectory of the pandemic and labour market recovery, these two factors in conjunction with the fact that social grant receipt and employment are not mutually exclusive (nearly half of all CSG caregivers are employed)[17] suggest that a top-up to the CSG may go a long way towards redressing widening gender wage inequality at the bottom of the wage distribution.

º Own calculations using NIDS Wave 5 (2017).

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Tables

Table 1: Employment, wages, working hours, and childcare hours by gender: February and June 2020

	February 2020			June 2020		
	Male	Female	Difference	Male	Female	Difference
Panel (a): Cross-sectional samples						
Employment	10 100 000 (605 858)	8 780 629 (523 840)	-1 319 371***	8 858 034 (553 672)	7 106 318 (453 108)	-1 751 716***
Mean real monthly wage	9 791.88 (934.19)	5 819.50 (407.08)	-3 972.39***	11 287.11 (1 121.54)	6 613.10 (668.56)	-4 674.01***
Mean weekly working hours	39.47 (0.71)	36.06 (0.64)	-3.41***	41.39 (0.97)	39.05 (1.09)	-2.34
Mean daily childcare hours	9.69 (0.54)	11.34 (0.36)	1.65***	6.66 (0.39)	12.00 (0.39)	5.34***
Panel (b): Employed in both periods						
Mean real monthly wage	11 484.69 (1 308.38)	7 422.57 (678.81)	-4 062.12***	12 256.66 (1 309.91)	7 268.81 (748.09)	-4 987.85***
Mean weekly working hours	41.59 (0.84)	38.70 (0.83)	-2.89**	41.98 (1.06)	39.58 (1.18)	-2.4
Mean daily childcare hours	9.35 (0.82)	10.61 (0.69)	1.26	5.64 (0.58)	9.54 (0.73)	3.9***

Authors' own calculations. Source: NIDS-CRAM Waves 1 and 2.
Notes: Within-wave samples restricted to employed individuals aged 18-64 years. Estimates are weighted using sampling weights, except for wage estimates which are weighted using computed bracket weights. Estimates account for complex survey design. Clustered standard errors presented in parentheses. Wages expressed in April 2021 Rands. Childcare hours data for February 2020 not available in the dataset; imputed estimate presented which was calculated using data from the Wave 2 items: "*In April, did you personally spent more time than usual looking after children?*" and "*How much more time did you spend per day?*". Adjusted Wald test used to determine statistical significance of between-gender differences. Statistical significance levels as follows: * p<0.1; ** p<0.05; *** p<0.01.

Table 2: Unconditional monthly gender wage gaps by group, February and June 2020

	February 2020				June 2020			
	Male	Female	Ratio (F/M)		Male	Female	Ratio (F/M)	
Overall	9 791.88	5 819.50	0.59	***	11 287.11	6 613.10	0.59	***
Age group								
18-34	6 529.02	4 844.06	0.74	**	7 518.54	5 802.77	0.77	
35-49	12 421.29	6 522.49	0.53	***	13 574.01	6 566.04	0.48	***
50-64	12 839.75	7 092.30	0.55		17 364.00	16 570.54	0.95	
Race								
Black African	7 244.10	4 029.55	0.56	***	9 042.18	4 955.35	0.55	***
Coloured	6 420.40	7 240.70	1.13		10 027.39	5 953.91	0.59	
Indian/Asian	8 537.44	4 506.01	0.53		7 232.63	5 967.89	0.83	
White	30 021.18	16 750.96	0.56	***	25 967.83	16 790.22	0.65	*
Education								
Up to primary	2 900.92	1 935.11	0.67	*	5 050.66	1 940.28	0.38	***
Up to secondary	4 418.23	2 909.98	0.66	**	7 183.72	3 086.22	0.43	*
Complete secondary	7 293.53	3 987.18	0.55	***	9 818.78	4 475.53	0.46	***
Tertiary	20 347.86	10 215.38	0.50	***	18 614.14	11 670.88	0.63	***
Occupation								
Managers	21 547.47	11 899.17	0.55	*	20 860.70	17 943.41	0.86	
Professionals	26 439.43	13 160.83	0.50	***	28 373.16	13 867.48	0.49	***
Technicians professionals	9 794.03	10 354.65	1.06		14 135.19	3 912.58	0.28	***
Clerical support workers	4 656.16	6 364.58	1.37		5 133.90	6 399.34	1.25	
Service and sales workers	7 082.86	3 104.26	0.44	***	6 053.79	3 561.31	0.59	***
Skilled agricultural workers	3 582.06	1 688.18	0.47	*	3 944.45	2 084.77	0.53	*
Craft and related trades workers	5 158.20	2 414.02	0.47	***	7 467.58	5 575.64	0.75	
Plant and machine operators	8 907.49	3 620.07	0.41	***	9 472.16	5 757.86	0.61	**
Elementary occupations	3 640.20	2 370.91	0.65	*	5 128.16	2 667.73	0.52	***
Real monthly wage quintile								

Poorest 20%	369.63	364.78	0.99		463.76	737.63	1.59	***
2	1 782.54	1 759.47	0.99		2 622.54	2 615.99	1.00	
3	3 801.08	3 743.08	0.98		4 601.49	4 418.47	0.96	
4	7 417.67	7 198.96	0.97		9 110.23	9 456.63	1.04	
Richest 20%	29 919.52	21 687.03	0.72	***	32 952.99	25 871.02	0.79	*

Authors' own calculations. Source: NIDS-CRAM Waves 1 and 2.
Notes: Within-wave samples restricted to employed individuals aged 18-64 years. Estimates are weighted using computed bracket weights. Estimates account for complex survey design. Wages expressed in monthly April 2021 Rands. Ratio calculated as the mean monthly wage for women as a share of that of men. Adjusted Wald test used to determine statistical significance of between-gender differences. Statistical significance levels as follows: * p<0.1; ** p<0.05; *** p<0.01.

Table 3: Unconditional and conditional Mincerian OLS regression estimates of the monthly gender wage gap, February and June 2020

	February 2020		June 2020	
Sample: Cross-sectional samples	(1)	(2)	(3)	(4)
Female	-0.371***	-0.374***	-0.595***	-0.512***
	(0.088)	(0.070)	(0.104)	(0.078)
Controls	N	Y	N	Y
Constant	8.374***	4.483***	8.803***	6.119***
	(0.076)	(0.518)	(0.080)	(0.646)
N	2 474	1 931	1 577	1 010
R^2	0.018	0.546	0.061	0.527
Sample: Employed in both periods	(5)	(6)	(7)	(8)
Female	-0.356***	-0.338***	-0.535***	-0.470***
	(0.113)	(0.077)	(0.111)	(0.080)
Controls	N	Y	N	Y
Constant	8.644***	4.430***	8.886***	5.778***
	(0.093)	(0.637)	(0.091)	(0.544)
N	1 382	1 090	1 302	868
R^2	0.019	0.574	0.053	0.563

Authors' own calculations. Source: NIDS-CRAM Waves 1 and 2.
Notes: Within-wave samples restricted to employed individuals aged 18-64 years. Estimates are weighted using computed bracket weights and account for complex survey design. Clustered standard errors presented in parentheses. Vector of demographic control variables include sex, age (years), age squared, self-reported race, highest level of education, marital status, geographic area, province of residence, home language, number of household members younger than 18 years, and a dummy variable for living with at least one child younger than 7 years. Vector of labour control variables include main occupation and weekly working hours. Statistical significance levels as follows: * p<0.1; ** p<0.05; *** p<0.01.

Table 4: Estimates of the conditional gender wage gap in February 2020 and June 2020, by model specification

Quantile	Pooled cross-section		DFL reweighting		Panel	
	February 2020	June 2020	February 2020	June 2020	February 2020	June 2020
5	-0.10	-0.63***	-0.10	-0.59***	-0.18	-0.77***
10	-0.04	-0.65***	-0.04	-0.48***	-0.42**	-0.71***
15	-0.27**	-0.53***	-0.27**	-0.54***	-0.31**	-0.50***
20	-0.37***	-0.49***	-0.37***	-0.57***	-0.24*	-0.48***
25	-0.27***	-0.57***	-0.27***	-0.58***	-0.43***	-0.48***
30	-0.38***	-0.43***	-0.38***	-0.52***	-0.40***	-0.26**
35	-0.38***	-0.35***	-0.38***	-0.39***	-0.25**	-0.36***
40	-0.46***	-0.33***	-0.46***	-0.41***	-0.27***	-0.27***
45	-0.30***	-0.46***	-0.30***	-0.40***	-0.21*	-0.38***
50	-0.28***	-0.53***	-0.28***	-0.62***	-0.22	-0.38***
55	-0.26***	-0.46***	-0.26***	-0.49***	-0.33**	-0.31**
60	-0.36***	-0.45***	-0.36***	-0.41***	-0.35**	-0.47***
65	-0.44***	-0.57***	-0.44***	-0.48***	-0.49***	-0.59***
70	-0.59***	-0.70***	-0.59***	-0.57***	-0.52***	-0.61***
75	-0.72***	-0.50***	-0.72***	-0.66***	-0.57***	-0.35*

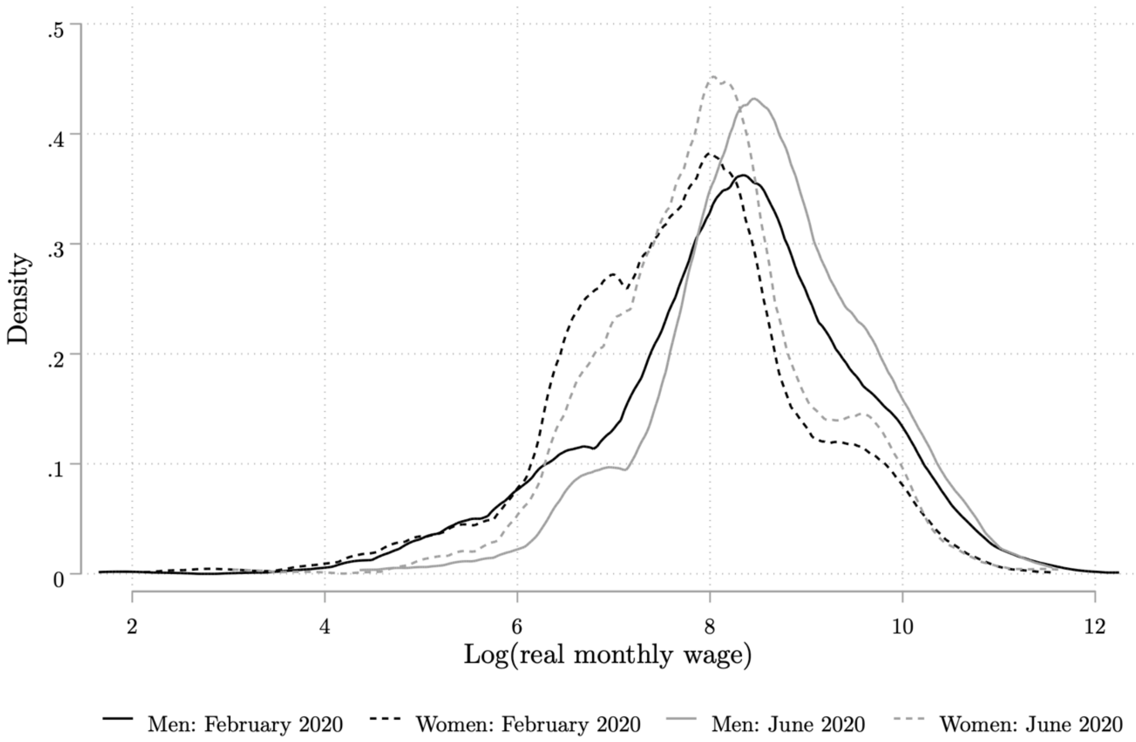
80	-0.61***	-0.32*	-0.61***	-0.56***	-0.37**	-0.38***
85	-0.50***	-0.47***	-0.50***	-0.47***	-0.29*	-0.49***
90	-0.49***	-0.55***	-0.49***	-0.56***	-0.29*	-0.57***
95	-0.35**	-0.59***	-0.35**	-0.71***	-0.21	-0.70***

Source: NIDS-CRAM Waves 1 and 2. Authors' own calculations.

Notes: Variables controlled for in regressions include age, age squared, race, highest level of education, main occupation, area of residence, province, home language, marital status, number of cohabiting children under age 18, and weekly hours worked. Point estimates are the coefficient on the female dummy in the relevant RIF regression at a given quantile. Significance levels reported for t-test of whether coefficient = 0. * p<0.1; ** p<0.05; *** p<0.01. Estimates weighted according to relevant bracket weight, or in the case of DFL reweighted estimates, the DFL-adjusted bracket weight. Estimates adjusted for complex survey design. Wages inflated to April 2021 Rands.

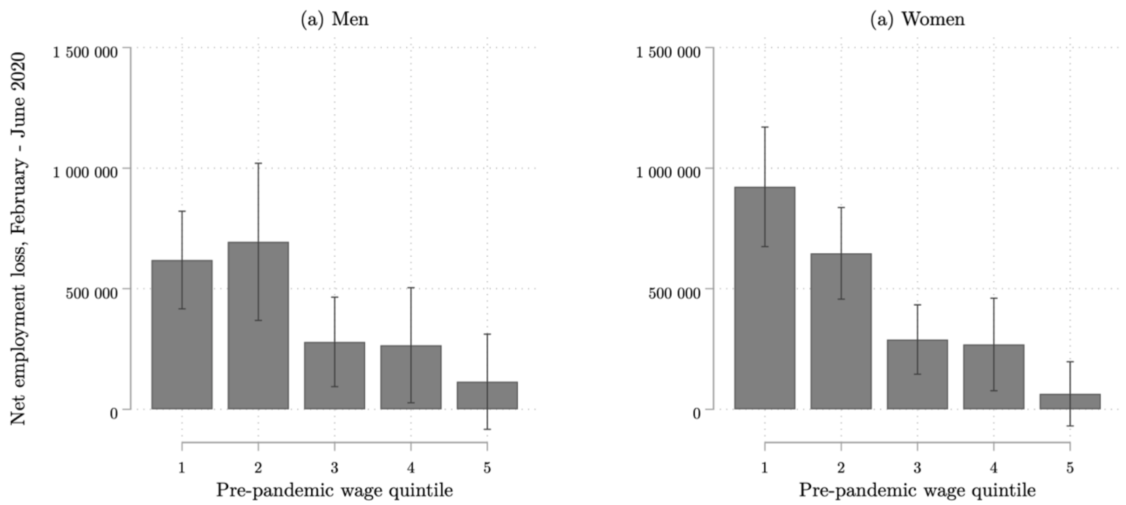
Figures

Figure 1: Real monthly wage distributions by gender, February 2020 and June 2020



Authors' own calculations. Source: NIDS-CRAM Waves 1 and 2.
Notes: Within-wave samples restricted to employed individuals aged 18-64 years. Estimates are weighted using panel sampling weights and account for complex survey design. Wage quintiles estimated using pre-pandemic (February 2020) real monthly wages and computed bracket weights.

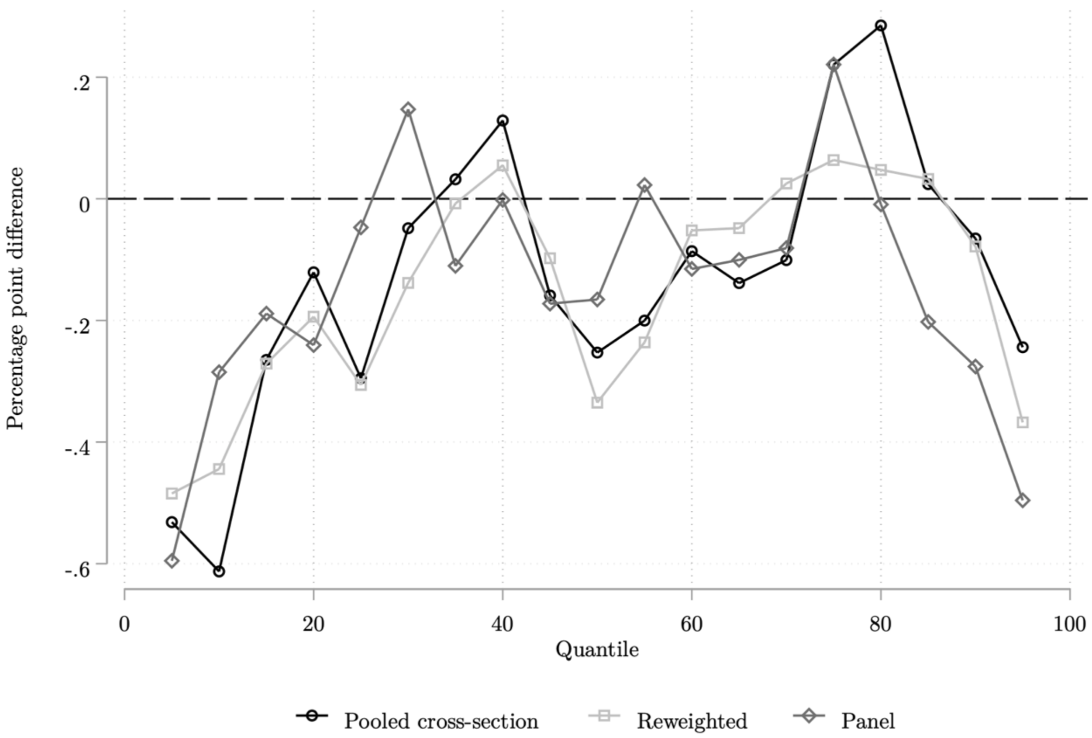
Figure 2: Net employment loss by gender and pre-pandemic wage quintile, February 2020 to June 2020



Authors' own calculations. Source: NIDS-CRAM Waves 1 and 2.

Notes: Within-wave samples restricted to employed individuals aged 18-64 years. Estimates are weighted using panel sampling weights and account for complex survey design. Capped spikes represent 95% confidence intervals. Wage quintiles estimated using pre-pandemic (February 2020) real monthly wages and computed bracket weights.

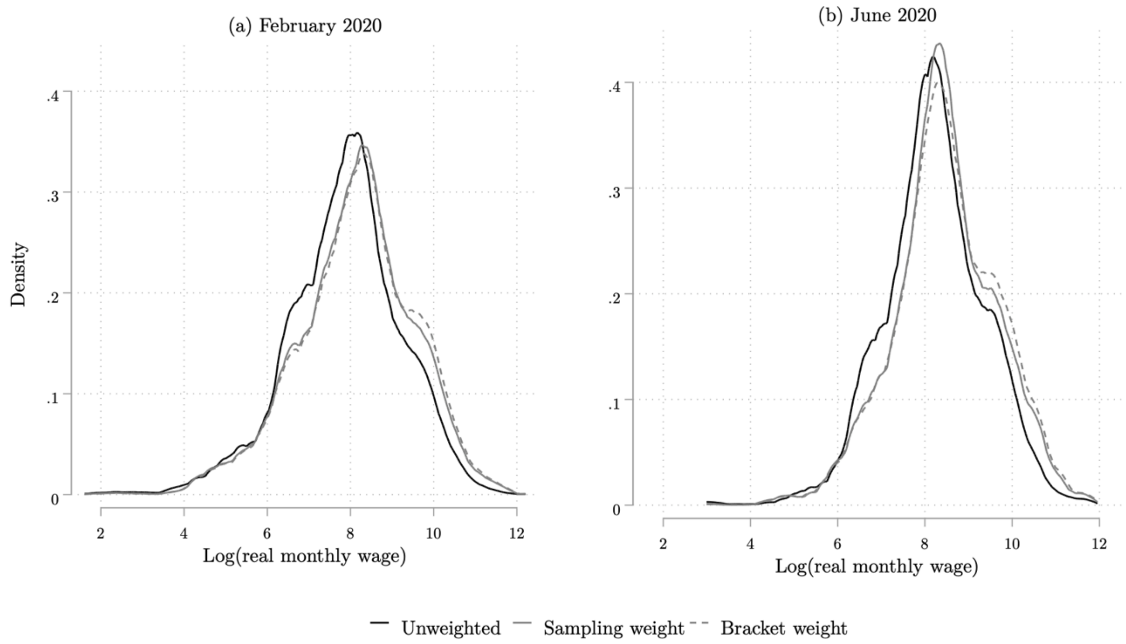
Figure 3: Difference in monthly gender wage gap estimates between February and June 2020



Source: NIDS-CRAM Waves 1 and 2. Authors' own calculations.
Notes: Variables controlled for in regressions include age, age squared, race, highest level of education, main occupation, area of residence, province, home language, marital status, number of cohabiting children under age 18, and weekly hours worked. Point estimates of differences are calculated as coefficient in June minus coefficient in February at each given quantile. Estimates weighted according to relevant bracket weight, or in the case of DFL reweighted estimates, the DFL-adjusted bracket weight. Estimates adjusted for complex survey design. Wages inflated to April 2021 Rands.

Appendix

Figure A1: Real monthly wage distributions, February and June 2020: unweighted versus sampling weighted versus bracket weighted



Authors' own calculations. Source: NIDS-CRAM Waves 1 and 2.
Notes: Within-wave samples restricted to employed individuals aged 18-64 years.

Table A1: Probability of reporting an actual Rand amount by wage bracket and wave

Monthly wage bracket	February 2020	June 2020
Zero/nothing	0.639	0.945
< R3 000	0.853	0.879
R3 001 to R6 000	0.831	0.932
R6 001 to R12 000	0.865	0.871
R12 001 to R24 000	0.735	0.762
> R24 000	0.756	0.771

Authors' own calculations. Source: NIDS-CRAM Waves 1 and 2.
Notes: Within-wave samples restricted to employed individuals aged 18-64 years.

Table A2: Complete unconditional and conditional Mincerian OLS regression estimates of the monthly gender wage gap: February and June 2020

Period:	February 2020 (pre-lockdown)				June 2020 (during lockdown)			
Sample:	Cross sectional		Employed in both periods		Cross sectional		Employed in both periods	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	-0.371***	-0.374***	-0.356***	-0.338***	-0.595***	-0.512***	-0.535***	-0.470***
	(0.088)	(0.070)	(0.113)	(0.077)	(0.104)	(0.078)	(0.111)	(0.080)
Age		0.110***		0.080***		0.035		0.053***
		(0.027)		(0.025)		(0.022)		(0.020)
Age squared		-0.001***		-0.001**		-0.000		-0.000*
		(0.000)		(0.000)		(0.000)		(0.000)
Coloured		-0.058		-0.429*		-0.277		-0.200

	(0.198)	(0.237)	(0.174)	(0.173)
Asian/Indian	-0.274	-0.824**	-0.318	-0.230
	(0.313)	(0.398)	(0.270)	(0.217)
White	0.516**	0.044	0.047	-0.001
	(0.210)	(0.209)	(0.182)	(0.181)
Urban	0.221**	0.283**	0.281***	0.320***
	(0.105)	(0.127)	(0.095)	(0.100)
Farms	-0.079	0.057	0.089	0.165
	(0.214)	(0.291)	(0.233)	(0.272)
Up to Secondary	0.192	0.430**	0.490***	0.447***
	(0.144)	(0.176)	(0.160)	(0.156)
Matric	0.442***	0.748***	0.801***	0.806***
	(0.157)	(0.175)	(0.158)	(0.155)
Tertiary	1.029***	1.211***	1.188***	1.202***
	(0.169)	(0.198)	(0.151)	(0.147)
Eastern Cape	0.022	0.107	-0.203	-0.051
	(0.146)	(0.152)	(0.196)	(0.189)
Northern Cape	0.169	0.059	-0.231	-0.109
	(0.148)	(0.145)	(0.154)	(0.145)
Free State	-0.120	0.082	-0.256	-0.119
	(0.158)	(0.167)	(0.239)	(0.231)
KwaZulu-Natal	-0.344**	-0.222	-0.105	0.054
	(0.167)	(0.166)	(0.201)	(0.201)
North West	-0.145	-0.094	-0.109	0.205
	(0.210)	(0.252)	(0.201)	(0.207)
Gauteng	0.014	0.183	-0.093	0.005
	(0.124)	(0.118)	(0.165)	(0.163)
Mpumalanga	0.001	0.091	-0.155	0.003
	(0.172)	(0.156)	(0.194)	(0.197)
Limpopo	0.035	0.330	-0.091	0.091
	(0.237)	(0.299)	(0.222)	(0.234)
Married	0.133**	0.182**	0.289***	0.310***
	(0.061)	(0.090)	(0.076)	(0.076)
isiXhosa	0.505**	0.659**	1.068***	0.932***
	(0.217)	(0.264)	(0.346)	(0.268)
isiZulu	0.602***	0.710***	1.018***	0.912***
	(0.181)	(0.251)	(0.316)	(0.248)
Sepedi	0.318*	0.318	0.932***	0.825***
	(0.188)	(0.285)	(0.339)	(0.297)
Sesotho	0.488***	0.470*	0.867**	0.705***
	(0.177)	(0.249)	(0.343)	(0.257)
Setswana	0.327	0.146	1.026***	0.696***
	(0.202)	(0.270)	(0.336)	(0.246)
siSwati	0.131	0.467	0.917**	0.870***
	(0.253)	(0.325)	(0.382)	(0.322)
Tshivenda	0.494	0.579	0.996***	0.886***
	(0.324)	(0.369)	(0.333)	(0.294)
Xitsonga	0.158	0.186	0.843***	0.706***
	(0.189)	(0.236)	(0.323)	(0.253)
Afrikaans	0.434*	0.876***	1.040***	0.958***
	(0.243)	(0.234)	(0.348)	(0.282)
English	0.561***	0.887***	1.022***	0.898***
	(0.206)	(0.232)	(0.336)	(0.266)
Number of children (<18 years) in household	-0.019	-0.042*	-0.019	-0.017
	(0.019)	(0.022)	(0.018)	(0.019)
Number of young children (<7 years) in household	-0.063	0.041	0.036	0.073
	(0.070)	(0.088)	(0.078)	(0.084)
Managers	-0.038	0.273	0.172	0.038
	(0.197)	(0.214)	(0.303)	(0.287)

Professionals		0.117		0.431*		-0.027		-0.098
		(0.200)		(0.234)		(0.308)		(0.292)
Technicians and associate professionals		-0.187		0.163		-0.908***		-0.882***
		(0.189)		(0.280)		(0.292)		(0.272)
Clerical support workers		-0.592***		-0.318*		-0.484*		-0.609**
		(0.171)		(0.182)		(0.272)		(0.247)
Service and sales workers		-0.910***		-0.469**		-0.746***		-0.851***
		(0.178)		(0.205)		(0.263)		(0.233)
Skilled agricultural workers		-0.836***		-0.330		-0.847***		-0.933***
		(0.243)		(0.270)		(0.314)		(0.332)
Craft and related trades workers		-0.894***		-0.556**		-0.427		-0.662**
		(0.211)		(0.251)		(0.304)		(0.285)
Plant and machine operators		-0.532***		-0.259		-0.469*		-0.614**
		(0.201)		(0.228)		(0.271)		(0.250)
Elementary occupations		-1.038***		-0.834***		-0.798***		-0.999***
		(0.185)		(0.192)		(0.269)		(0.241)
Weekly working hours		0.023***		0.019***		0.009***		0.010***
		(0.002)		(0.003)		(0.002)		(0.002)
Constant	8.374***	4.483***	8.644***	4.430***	8.803***	6.119***	8.886***	5.778***
	(0.076)	(0.518)	(0.093)	(0.637)	(0.080)	(0.646)	(0.091)	(0.544)
N	2 474	1 931	1 382	1 090	1 577	1 010	1 302	868
R^2	0.018	0.546	0.019	0.574	0.061	0.527	0.053	0.563

Authors' own calculations. Source: NIDS-CRAM Waves 1 and 2.

Notes: Within-wave samples restricted to employed individuals aged 18-64 years. Estimates are weighted using computed bracket weights and account for complex survey design. Clustered standard errors presented in parentheses. Reference groups for categorical variables as follows: African/black, Traditional area, up to primary level education, Western Cape, isiNdebele home language, Armed forces main occupation. Statistical significance levels as follows: * p<0.1; ** p<0.05; *** p<0.01.

Table A3: Unconditional and conditional Mincerian OLS regression estimates of the hourly gender wage gap: February and June 2020

	February 2020 (pre-lockdown)		June 2020 (during lockdown)	
Sample: Cross-sectional samples	(1)	(2)	(3)	(4)
Female	-0.298***	-0.380***	-0.595***	-0.512***
	(0.092)	(0.066)	(0.104)	(0.078)
Controls	N	Y	N	Y
Constant	3.363***	0.919*	8.803***	6.119***
	(0.078)	(0.483)	(0.080)	(0.646)
N	2 318	1 931	1 577	1 010
R^2	0.014	0.495	0.061	0.527
Sample: Employed in both periods	(5)	(6)	(7)	(8)
Female	-0.320***	-0.348***	-0.535***	-0.470***
	(0.117)	(0.074)	(0.111)	(0.080)
Controls	N	Y	N	Y
Constant	3.573***	0.790	8.886***	5.778***
	(0.098)	(0.606)	(0.091)	(0.544)
N	1 312	1 090	1 302	868
R^2	0.017	0.569	0.053	0.563

Authors' own calculations. Source: NIDS-CRAM Waves 1 and 2.

Notes: Within-wave samples restricted to employed individuals aged 18-64 years. Estimates are weighted using computed bracket weights and account for complex survey design. Clustered standard errors presented in parentheses. Vector of control variables include sex, age (years), age squared, self-reported race, highest level of education, marital status, geographic area, province of residence, home language, number of household members younger than 18 years, a dummy variable for living with at least one child younger than 7 years, and main occupation. Statistical significance levels as follows: * p<0.1; ** p<0.05; *** p<0.01.

Table A4: Percentage point difference in monthly gender wage gap estimates, February to June 2020

Quantile	Pooled cross-section	DFL Reweighting	Panel
5	-0.53**	-0.48**	-0.60***
10	-0.61***	-0.44**	-0.28*
15	-0.26*	-0.27*	-0.19
20	-0.12	-0.19	-0.24*
25	-0.29**	-0.31**	-0.05
30	-0.05	-0.14	0.15
35	0.03	-0.01	-0.11
40	0.13	0.06	0.00
45	-0.16	-0.10	-0.17*
50	-0.25**	-0.34***	-0.17*
55	-0.20*	-0.24**	0.02
60	-0.09	-0.05	-0.12
65	-0.14	-0.05	-0.10
70	-0.10	0.03	-0.08
75	0.22	0.06	0.22
80	0.29	0.05	-0.01
85	0.02	0.03	-0.20
90	-0.07	-0.08	-0.28
95	-0.24	-0.37	-0.50**

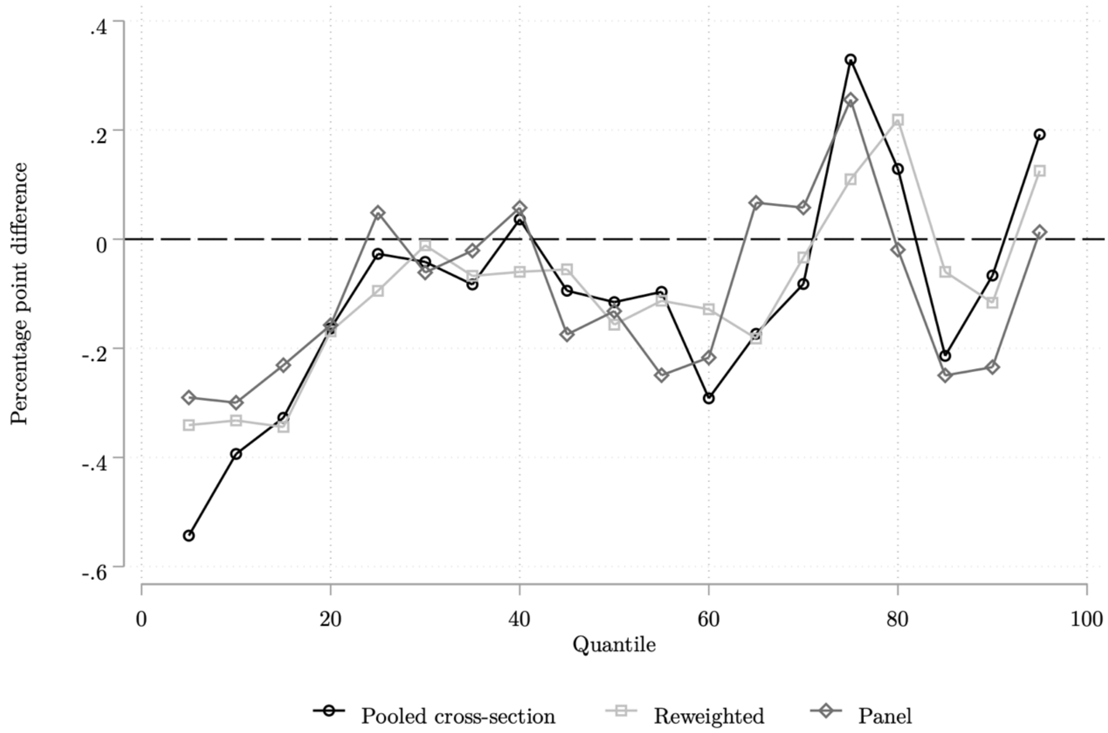
Source: NIDS-CRAM Waves 1 and 2. Authors' own calculations.
Notes: Variables controlled for in regressions include age, age squared, race, highest level of education, main occupation, area of residence, province, home language, marital status, number of cohabiting children under age 18, and weekly hours worked. Point estimates of differences are calculated as coefficient in June minus coefficient in February at each given quantile. Significance levels reported for Wald test of whether difference in coefficients equals 0. * p<0.1; ** p<0.05; *** p<0.01. Estimates weighted according to relevant bracket weight, or in the case of DFL reweighted estimates, the DFL-adjusted bracket weight. Estimates adjusted for complex survey design. Wages inflated to April 2021 Rands.

Table A5: Percentage point difference in hourly gender wage gap estimates, February to June 2020

Quantile	Pooled cross-section	DFL Reweighting	Panel
5	-0.54**	-0.34	-0.29
10	-0.39**	-0.33*	-0.30*
15	-0.33**	-0.34**	-0.23
20	-0.16	-0.17	-0.16
25	-0.03	-0.09	0.05
30	-0.04	-0.01	-0.06
35	-0.08	-0.07	-0.02
40	0.04	-0.06	0.06
45	-0.09	-0.06	-0.17*
50	-0.12	-0.16	-0.13
55	-0.10	-0.11	-0.25**
60	-0.29***	-0.13	-0.22**
65	-0.17	-0.18	0.07
70	-0.08	-0.03	0.06
75	0.33**	0.11	0.26*
80	0.13	0.22	-0.02
85	-0.21	-0.06	-0.25
90	-0.07	-0.12	-0.23
95	0.19	0.13	0.01

Source: NIDS-CRAM Waves 1 and 2. Authors' own calculations.
Notes: Variables controlled for in regressions include age, age squared, race, highest level of education, main occupation, area of residence, province, home language, marital status, number of cohabiting children under age 18, and weekly hours worked. Point estimates of differences are calculated as coefficient in June minus coefficient in February at each given quantile. Significance levels reported for Wald test of whether difference in coefficients equals 0. * p<0.1; ** p<0.05; *** p<0.01. Estimates weighted according to relevant bracket weight, or in the case of DFL reweighted estimates, the DFL-adjusted bracket weight. Estimates adjusted for complex survey design. Wages inflated to April 2021 Rands.

Figure A2: Difference in hourly gender wage gap estimates between February and June 2020



Source: NIDS-CRAM Waves 1 and 2. Authors' own calculations.
Notes: Variables controlled for in regressions include age, age squared, race, highest level of education, main occupation, area of residence, province, home language, marital status, number of cohabiting children under age 18, and weekly hours worked. Point estimates of differences are calculated as coefficient in June minus coefficient in February at each given quantile. Estimates weighted according to relevant bracket weight, or in the case of DFL reweighted estimates, the DFL-adjusted bracket weight. Estimates adjusted for complex survey design. Wages inflated to April 2021 Rands.