THE NATIONAL
MINIMUM WAGE REPORT

Measuring the impact of the 2023 national minimum wage increase

A report for the National Minimum Wage Commission

employment & labour

Department:
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Development Policy Research Unit (DPRU)

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Executive Summary

This report is focused on the labour market impacts of the National Minimum Wage (NMW) increase that became effective on the 1st of March 2023. The updated minimum wage was set at R25.42 per hour – a nominal increase of 9.6% from the previous year – and applies to all employees in South Africa.[1] To measure the effects of this change, we use individual-level data from Statistics South Africa's (StatsSA) Quarterly Labour Force Survey (QLFS) covering the period 2022Q2-2023Q2. The period includes five quarters of data – four quarters prior to the wage change and one quarter following it – and, as such, this analysis focuses only on the immediate effects of the NMW adjustment.

We aim to measure changes in wages, employment, and working hours and estimate to what extent any observed changes can reasonably be attributed to the new, higher wage floor. In addition, we test for effects on non-compliance. To isolate the effect of the policy itself on our outcomes of interest, we adopt a Difference-in-Differences (DiD) design on three empirical strategies: (i) We use the full cross-sectional QLFS dataset and exploit geographic variation in relative wages before the NMW change; (ii) We make use of the panel feature of the data by using a subsample of the QLFS that follows the same employees over time, and exploit variation in 'wage gaps' calculated as is the difference between their hourly wage and the incoming NMW; (iii) We again use the panel feature of the data and compare the outcomes of low-wage and high-wage workers from before to after the NMW increase, in which high wage workers earn sufficiently more than the NMW to be unaffected by the legislated increase. Relying on a combination of approaches gives us more confidence in the results we report and allows for additional specificity when interpreting the findings.

Our results suggest that the NMW increase had a clear, positive wage effect, which remains consistent across all our specifications. These wage effects appear stronger at the bottom of the earnings distribution. Consistent with this wage increase, we observe small reductions in both the level and depth of non-compliance. Regarding employment effects, our results are mixed. Using the first approach (i) which uses the full cross-sectional dataset and estimates effects at the district level, we do not find any evidence of an effect on employment. By contrast, when using the panel sample with approaches (ii) and (iii), we find a small, negative impact on employment. The findings for working hours are similarly equivocal, suggesting either no significant change or a marginal reduction in weekly working hours. We provide a short summary of the main findings below.

[1] The only exception being those employed as part of the Expanded Public Works Programme (EPWP).

Main Findings

Wage Effects

- Substantial wage effects are observed across all empirical specifications, as well as in our event study design which examines wave-specific changes.
- We find average real hourly wage increases attributable to the NMW hike that vary between 11-21%, depending on the sample of workers included in the data and empirical specification.
- Additional estimates for employees in Domestic Work and Agriculture reveal small positive wage increases relative to other covered workers.

Employment Effects

- In our main specification, which includes all workers in the QLFS sample, we do not find any evidence that the NMW hike had any statistically significant effect on employment.
- However, our panel approaches using two different specifications suggest that the NMW had a small, negative effect on employment.
- The size of this latter negative effect is, however, small but variable, dependent on the sample and empirical specification.

Working Hours Effects

- Overall, we do not find consistent evidence that the NMW hike had any effect on working hours.
- In our main specification, which includes all workers in the QLFS sample, we find that the NMW hike had no effect on working hours. The same result is found in our first panel specification.
- In our second panel approach, however, which compares outcomes between low- and high-wage workers, we find a small but statistically significant decrease in working hours.

Non-Compliance Effects

- Related to the strong evidence of positive wage effects, we estimate statistically significant, negative effects on non-compliance.
- Our results suggest that the NMW hike reduced both the headcount and depth of non-compliance. Specifically, the NMW hike reduced non-compliance headcount by about 4% and depth by about 1%.
- The results suggest the hike resulted in fewer workers earning sub-minimum wages, and for those who remained earning below the NMW, the gap became more compressed.

1. Introduction

South Africa's National Minimum Wage (NMW) was raised on the 1st of March 2023 from R23.19 per hour to R25.42 per hour. It is the largest annual increase since the NMW was introduced at the beginning of 2019 – a nominal increase of 9.6%, or 2.5% in real terms.[2] This change affected approximately 37% of employees, or approximately 5 million workers, who were being paid below the new threshold before it came into force.[3] Notably, since 2022 Domestic and Agricultural workers have been subject to the general minimum wage rate, so this increase applies to all employees in the country apart from those employed in the government's public works program. The aim of this report is to provide an empirical account of the latest NMW change and determine if it has had any measurable labour market impacts for covered workers.

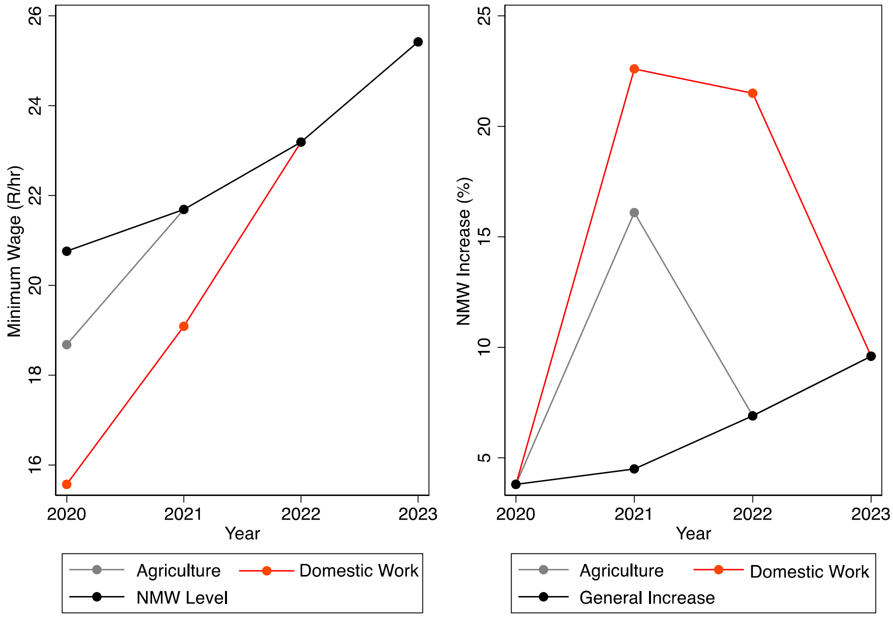
Since 2020, attempts to understand NMW impacts in South Africa have been compromised by two things: Firstly, the outsized effect that COVID-19 had on the labour market; and secondly, complications that the pandemic introduced for the collection of labour market data upon which any robust empirical analysis relies. Fortunately, as we show below, the main source of nationally representative labour market data – the Quarterly Labour Force Survey (QLFS) – has returned to its pre-pandemic state both in terms of data collection methods and the resulting sample included in the survey. We believe the sample to be sufficiently large for the analytical approaches we adopt, including approximately 15,000 employees in each wave. However, an important feature of this report is that it focuses on very short-term impacts, relying on only one quarter of data following the NMW increase.

For context, Figure 1 plots the level of the NMW since 2020 in the first panel, and the annual rate of increase in each year in the second panel. Rates for the Agricultural and Domestic Work sectors are shown separately until they equal the general NMW. It is clear the general NMW has increased consistently since 2020, with each annual update slightly higher than the previous year, and 2023 being the largest annual increase. Notably, for both the Agricultural and Domestic Work sectors minimum wage increases have been much higher to equalize these sectors with the general rate, where these have exceeded 15% and 20%, respectively. In this report, we are interested in the impact of the 2023 NMW increase for all covered workers, but we also run some sensitivity tests to see whether there are differential effects for workers in Agriculture and Domestic Work given the scale of cumulative minimum wage increases over the past few years.

[2] CPI headline inflation from March 2022-March 2023 was measured at 7.1% (StatsSA, 2023).

[3] This estimate is based on our own calculations using weighted (unimputed) QLFS wage data for the last quarter of 2022, after adjusting for outliers and missing data.

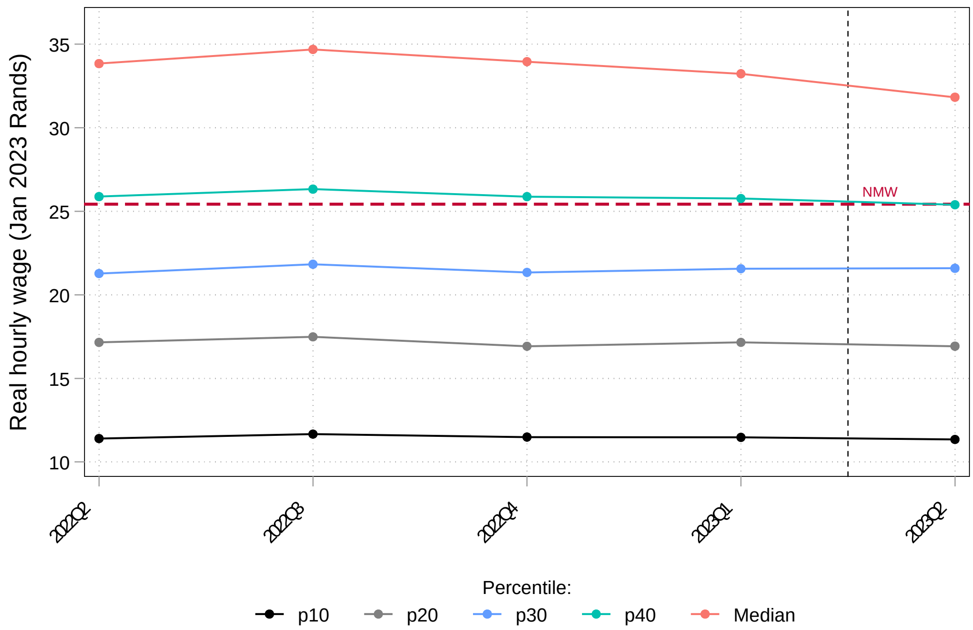
Figure 1. Annual National Minimum Wage Adjustments (Nominal R/hr): 2020-2023



Authors' own calculations. Source: Department of Employment and Labour (2023).
Note: The value of the NMW is shown in nominal terms, and we do not include the lower minimum wage rate for employees of the government's public works program.

The introduction of the NMW in the beginning of 2019 affected 38% of all employees in the South African labour market who were paid below the threshold of R20 before it came into force. On average, these affected employees were paid R12.10 in nominal terms before the NMW was introduced. Hence, under full compliance the hourly wage of the average affected worker should have increased by over 65%. Such an increase did not, however, materialise and hence minimum wage non-compliance continues to be evident in the labour market. Four years later in the beginning of 2023, the share of affected workers had only reduced marginally to 36.3%. As shown in Figure 2, which presents trends in inflation-adjusted hourly wages for various points of the wage distribution, this implies that the 2023 NMW of R25.42 per hour is situated just under the 40th percentile, equivalent to 76% of the median wage and 35% of the mean wage in the labour market, respectively.

Figure 2: Trends in real hourly wages across the wage distribution, 2022Q2 – 2023Q1



Authors' own calculations. Source: QLFS 2022Q2 – 2023Q2.
Notes: Sample restricted to working-aged (15-64 years) employees. Estimates weighted using sampling weights and account for the complex survey design. Raw, unimputed wage data provided by StatsSA and are adjusted for outliers and missing data. Shaded areas represented 95% confidence intervals. Horizontal line represents the level of the 2023 NMW of R25.42 per hour as of 1 March 2023. Vertical line distinguishes the periods before and after this increase.

There are a variety of approaches that can be used to try and estimate the effect of a minimum wage change on outcomes of interest. These are primarily determined by data availability and the structure of the policy change itself. For example, an almost ideal scenario is in the United States where available data allows one to follow the same individuals over time and minimum wages vary at the State level, making it possible to compare individual outcomes in response to a policy change both across States and over time. In South Africa, the availability of panel data is more limited, and in our case the NMW is implemented at the national-level and hence applies equally across all regions and all worker types, which restricts the kind of analytical approaches that are available to us.

We use three main approaches to assess the impact of the NMW increase, with each adopting a DiD technique to identify causal effects. These are explained in more detail in Section 4. To summarize: (i) Our first approach relies on district-level geographical variation in the share of workers directly affected prior to the 2023 increase, and tests whether labour market impacts were larger in districts with lower aggregate wages; (ii) In our second approach, we identify a sub-sample of workers who appear across multiple waves of the survey (the panel sample) and, focusing on sub-minimum wage workers, exploit variation in their wages relative to the incoming NMW level, otherwise known as a 'wage gap'; (iii) In our third approach, we again use the panel sample and compare the outcomes of a group of low-wage workers to those of a group of high-wage earners from before to after the NMW was increased. In all cases, our focus is testing for evidence of measurable effects on wages, employment, and working hours. Additionally, we are able to include estimates of effects on the level and depth of minimum wage non-compliance.

The rest of the report is structured as follows: Section 2 describes the data used and any adjustments we make to it, where an important element is our treatment of wages. We make use of the original QLFS wage data, which is different to the imputed data that is released publicly by StatsSA. Section 3 introduces several basic descriptive labour market trends and provides some context for the outcomes of interest in our analysis. Section 4 describes the empirical approaches we use to estimate the short-term labour market effects of the NMW increase. Section 5 presents our main results and some discussion of the relevant findings. Section 6 concludes with a short summary. Additional outputs are included in the Appendix.

2. Data

The data for our analysis come from the QLFS, a cross-sectional, nationally representative, household survey that is conducted by StatsSA every quarter.[4] It contains detailed information on labour market activities for individuals aged 15 years and older, including a wide range of demographic and socioeconomic characteristics for each respondent. Although the QLFS is most often used as a cross-sectional dataset, it does contain a panel component in which a subsample of the same individuals can be observed across multiple periods. As noted above, we exploit both aspects of the data in this report. The period of interest is from 2022Q2-2023Q2, which includes five quarters of data. In Figure 3 we plot the full, unweighted sample of individuals in the QLFS over this period, as well as the sample of the employed, which illustrates that the samples in the survey are now comparable in size relative to pre-pandemic levels.

[4] The survey follows a stratified two-stage sampling design, with probability proportional to size sampling of primary sampling units (PSU) in the first stage and sampling of dwelling units with systematic sampling in the second stage (Statistics South Africa, 2008). As such, the sampling unit is the dwelling and the unit of observation is the household. The sampling weights for the data account for original selection probabilities and non-response and are benchmarked to known population estimates of the entire civilian population of South Africa. We use these weights throughout the analysis to present population level estimates.

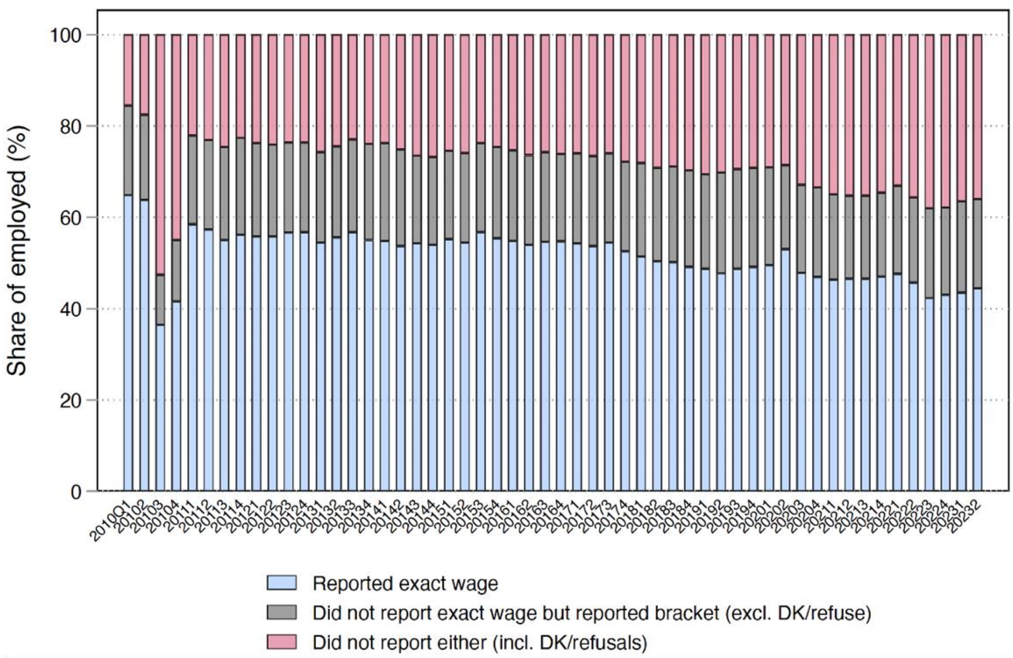
Figure 3. Unweighted QLFS Sample (2020Q1-2023Q2)

Authors' own calculations. Source: QLFS 2020Q1-2023Q2.
Note: Vertical line shows the timing of the onset of the COVID-19 pandemic which affected data collection for the QLFS and significantly reduced the sample size until 2022.

We adjust the QLFS data in various ways in order to create a dataset that is suitable for our purposes. Our sample is restricted to individuals of working age (15 – 64 years) and those who are wage earners or employees – that is, those who report working for someone else for pay. In the average wave, these workers represent the majority (83 percent) of workers in the country. We therefore exclude employers, the self-employed, and unpaid household workers. All our estimates are weighted using the relevant sampling weights provided by StatsSA and account for the complex survey design. We adjust our estimates for inflation using the quarterly CPI from StatsSA, benchmarking our estimates to January 2023, and present wages before taxation and deductions in real terms unless specified otherwise. Wages are converted to hourly values using data on reported 'usual weekly hours of work' at the individual-level. Following Wittenberg (2017) and Köhler and Bhorat (2023), outliers in the wage data are detected using the studentised regression residual technique and removed, however these account for less than 1% of the employed sample.

In addition to the standard adjustments described above, the wage data we use are different from the standard versions available in the public domain. All employed respondents in the QLFS are asked to report their earnings and may provide this information in three different ways. As shown in Figure 4, in recent years only about 50% of the employed sample provide enumerators with an actual Rand value for their earnings, while the other half either select an option from available 'earnings brackets', or simply do not provide any information. If the missing data from this latter two groups of semi or complete non-responders are not accounted for, any estimates of wages will be biased. The consequence is that some form of imputation must be used to estimate wage values for those employed individuals who do not report them, but for whom there is a range of detailed demographic and labour market information. We adopt a multiple imputation approach, considered as one of the most effective methods for addressing item non-response to date. This approach allows us to generate robust wage estimates for those respondents who only select a wage bracket, do not provide any information on their earnings, or are identified as outliers. Importantly, we are only able to do this as the wage data we use here is the raw, or unimputed, data acquired directly from StatsSA and not available in the public domain. Our data differs from the standard data that is released publicly in the annual Labour Market Dynamics South Africa (LMDSA) which contains wage imputations by StatsSA. This point is important because the imputations in the public release data are not distinguishable from reported Rand value observations, and significant problems have been identified with the imputation approach chosen by StatsSA, resulting in poor quality data and resultant estimates (Wittenberg, 2017; Kerr and Wittenberg, 2019; 2021; Bhorat et al., 2021; Köhler et al., 2023; Köhler, 2023; Köhler and Bhorat, 2023).

Figure 4. Distribution of wage responses among the employed in the QLFS, 2010Q1 – 2023Q2



Authors' own calculations. Source: QLFS 2010Q1 – 2023Q2.
Notes: Raw, unimputed wage data provided by StatsSA. Sample restricted to the working-age (15 to 64 years) employed. Unweighted estimates presented. DK = Don't know bracket responses.

Regarding the timing of both the QLFS and the NMW change, we use data on the month that each respondent was interviewed in order to divide individuals into 'pre' and 'post' groups for our analysis. The NMW is increased at the beginning of March in each year, and March falls into the first quarter of the survey (January-March). As a result, anyone surveyed in March will already be subject to the new NMW, so it is not possible to simply split the survey into quarterly time periods for analytical purposes. We obtain data from StatsSA on 'survey month' in order to split the sample more precisely. In the cross-sectional analysis, our preferred setup is that all individuals surveyed in March 2023 are combined with the cohort in 2023Q2 (April-June), where this group is counted as appearing in the period after the NMW has risen. We conduct sensitivity tests to examine how the timing of our 'post' sample affects our results.

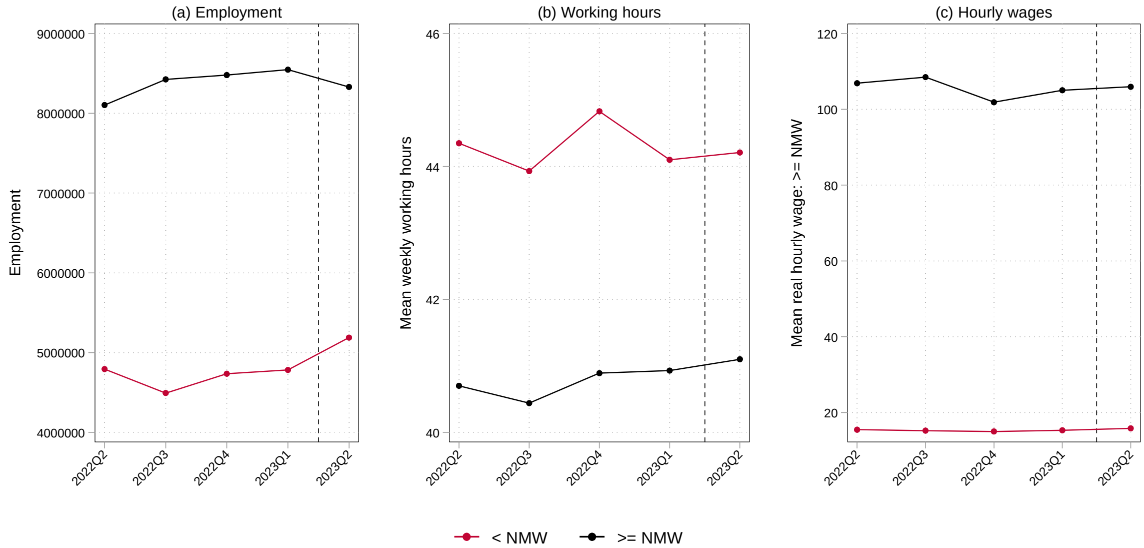
For the panel sample, because the survey is constructed on a quarterly basis and 75% of the sample is re-surveyed in each quarter, we cannot simply follow the above approach as it would result in some individuals appearing twice in the same 'period'. Instead, we define the 'post' period in the following way: where an individual appears in March 2023 and again in 2023Q2, we keep only their appearance in 2023Q2; however, if they are not re-surveyed in 2023Q2 they remain in the sample.

3. Descriptive Trends (2022Q2-2023Q2)

This section presents descriptive trends over the period as a precursor to the more detailed econometric approaches that follow. We begin with Figure 5 which provides an overview of trends in aggregate employment, working hours, and real hourly wages. The sample is divided into workers who earn either above or below the existing NMW. We do not control for changing sample composition and workers are allocated into each group within each survey wave.

An overall increase in total employment is evident over the period, both for workers earning above and below the NMW. Following the NMW increase, we observe opposing employment trends. This may or may not be the result of a higher NMW, leading to more workers being allocated into the sub-NMW group. Trends in working hours rise relatively consistently over time for those earning above the minimum wage, but the actual level change is small, and overall higher earners report working fewer hours per week. For sub-minimum wage earners, there is substantially more movement in the quarterly working hour trends, but we do not observe any meaningful changes on aggregate. Finally, trends in real mean hourly wages are relatively static for both low and high wage workers, with no obvious variation at this level of aggregation. Mean wages for those earning below the NMW rise marginally across the period from R15.49 to R15.85 per hour, while the mean for those above the NMW remains at around R106 per hour.

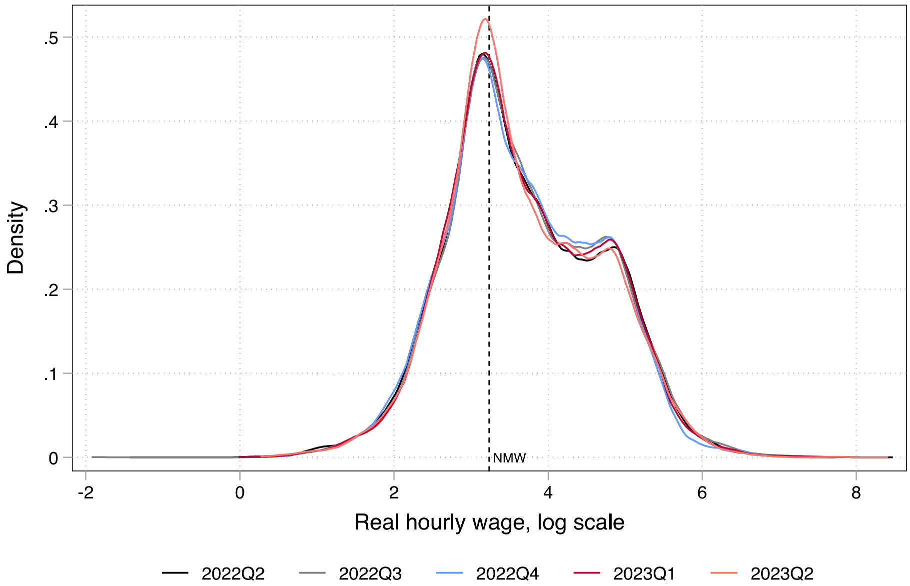
Figure 5. Trends in employment, working hours, and real hourly wages by NMW cut-off, 2022Q2 – 2023Q2



Authors' own calculations. Source: QLFS 2022Q2 – 2023Q2.
Notes: Sample restricted to working-aged (15-64 years) employees. Estimates weighted using sampling weights and account for the complex survey design. Raw, unimputed wage data provided by StatsSA and are adjusted for outliers and missing data. Shaded areas represented 95% confidence intervals. Vertical line distinguishes the periods before and after the 2023 NMW increase.

To get a more comprehensive picture of wage changes over time, Figure 6 presents the whole distribution of real hourly wages as opposed to just the mean above, on a log scale, in each survey wave for all employees. The level of the 2023 NMW is included as a vertical reference line. The wage distributions in the period leading up to the NMW change remain static, but there is a noticeable spike in 2023Q2, when the NMW was increased, around the level of the incoming NMW. This is an early, suggestive indication of a positive aggregate wage effect of the NMW hike.

Figure 6. Distribution of real log hourly wages: 2022Q2–2023Q2



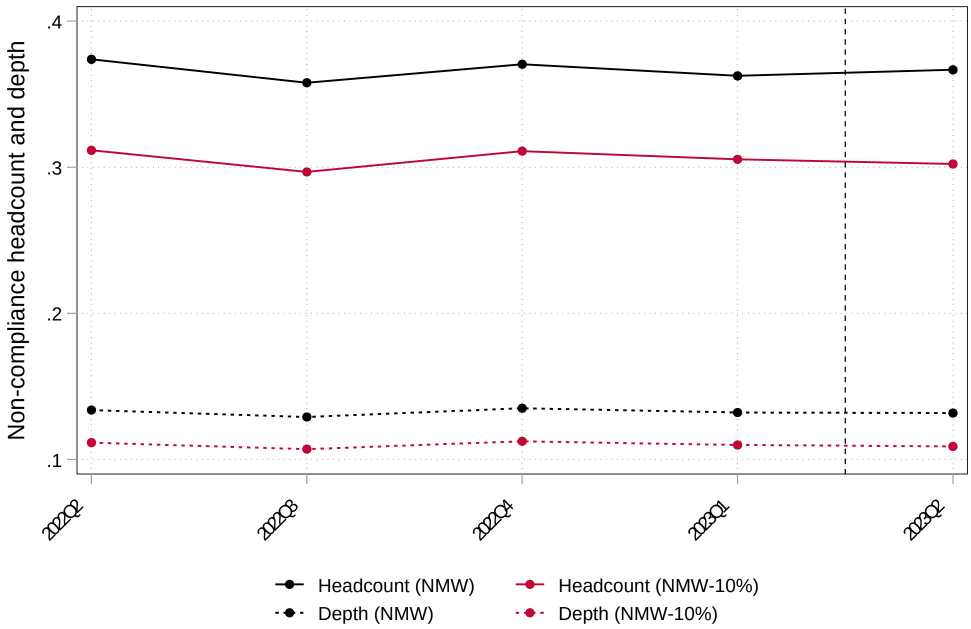
Authors' own calculations. Source: QLFS 2022Q2 – 2023Q2.
Notes: Sample restricted to working-aged (15-64 years) employees. Estimates weighted using sampling weights and account for the complex survey design. Raw, unimputed wage data provided by StatsSA and are adjusted for outliers and missing data. Vertical line represents the level of the new NMW as of 1 March 2023.

As is evident above and as previously mentioned, a large share of employees still earns below the new level of the NMW. Figure 7 presents estimates of two measures of minimum wage non-compliance: a headcount measure (the proportion of workers earning less than the NMW) and a depth measure (the average distance from the NMW, for workers earning less than the NMW). We plot two estimates in each case, where the black lines simply represent non-compliance based on reported hourly wages and can be seen as upper-bound estimates, while the red lines are more conservative.[5]

We observe a gradual decrease in aggregate non-compliance measures over the period, however the change is small. Focusing on the upper-bound estimates, non-compliance headcount reduced from 37.4% in 2022Q2 to 36.7% one year later in 2023Q2, however this difference is not statistically significantly different from zero. Similarly, non-compliance depth reduced from 13.4% to 13.2% over the period, but again this difference is not statistically significant. These marginal changes are similarly observed for the more conservative non-compliance measures. In Figure A1 in the Appendix, we disaggregate these trends by main industry and show that this decline in non-compliance is driven by Agriculture and, to a lesser extent, the Domestic Work industry. These two industries collectively comprise about one-third of all workers earning below the NMW. Additional estimates of non-compliance by region are presented in Section 4, at the district council level, and in the Appendix at the provincial level.

Figure 7: Trends in National Minimum Wage non-compliance, 2022Q2 – 2023Q2

[5] Our conservative estimates allow for a 10% decrease in the NMW cut-off level, taking into account some allowance for payments in-kind across sectors, the fact that we cannot accurately identify EPWP workers who are subject to a much lower NMW, and the possibility of some underreporting of wages.



Authors' own calculations. Source: QLFS 2022Q2 – 2023Q2.
Notes: Sample restricted to working-aged (15-64 years) employees. Estimates weighted using sampling weights and account for the complex survey design. Raw, unimputed wage data provided by StatsSA and are adjusted for outliers and missing data. Shaded areas represented 95% confidence intervals. Vertical line distinguishes the periods before and after the 2023 NMW increase.

4. Analytical Approach

The empirical literature on minimum wages in South Africa is relatively well developed and has produced a growing body of published research showcasing a variety of analytical techniques. This literature is homogenous in that every paper uses some form of DiD methodology to try to isolate the causal impact of the introduction of a minimum wage or an increase thereof on labour market and other outcomes. But the details of these empirical specifications vary widely, with each study using different data, regression specifications, and focusing on a range of outcomes. Taking this body of previous work into account, we draw on both the South African and international literature to develop a combination of analytical approaches that use both the cross-sectional and panel components of the QLFS data. Taking this combined approach gives us more confidence in the results we report and allows for additional specificity when interpreting our output.

4.1. Approach 1: Cross-sectional Data and Geographic Wage Variation

Our first empirical specification is informed by Bossler and Schank (2023) in their recently published study on the introduction of a NMW in Germany, which uses geographic variation in the share of sub-minimum wage workers to identify local labour markets where the minimum wage is likely to have more 'bite'. This approach is also comparable to previously published work on sectoral minimum wages in South Africa (Dinkelman and Ranchhod, 2012; Bhorat et al., 2013; Bhorat et al., 2014). In our case, we make use of variation in the share of sub-minimum wage workers across district councils before the 2023 NMW increase to identify expected bite, which is then used to estimate the effects of the policy after it comes into force. Intuitively, the theory predicts that districts with a higher proportion of sub-minimum wage workers will experience larger impacts from the NMW increase. Figure A3 in the Appendix indeed reveals higher average real wage growth from before to after the

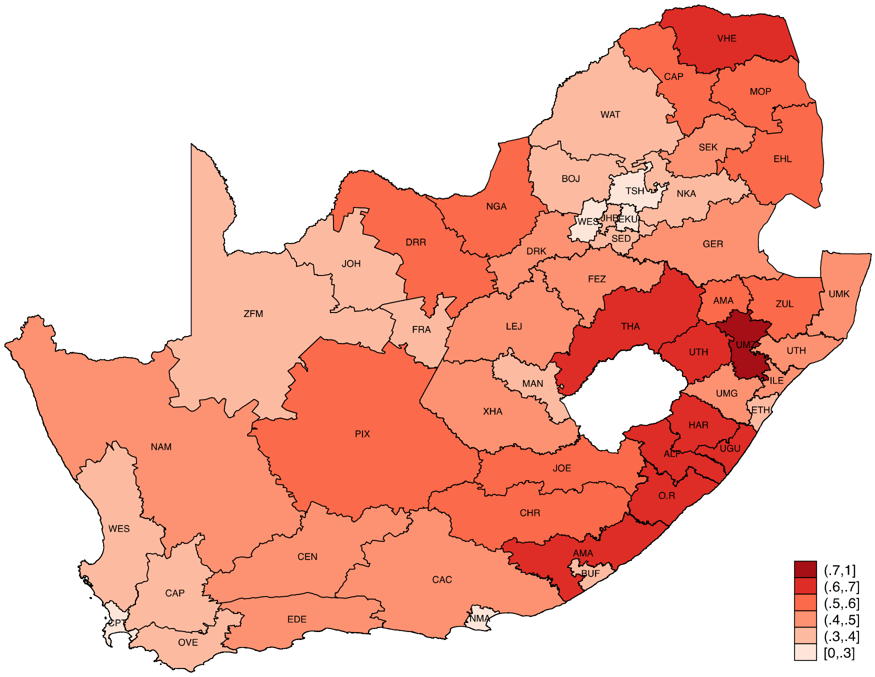
NMW hike among districts with higher proportions of sub-minimum wage workers prior to the hike, consistent with this theory.

As in Bossler and Schank (2023), we calculate the bite of the NMW as the proportion of employees in each district council who report earning less than the incoming NMW, in the period before it is implemented. Given that we have several waves of data in our 'pre' period, we use the average for the entire 'pre' period. The geographic distribution of this statistic is shown in Figure 8. District council-level 'bite' is grouped into six categories for representational purposes.[6] The lightly shaded areas indicate where less than 30% of employees earn below the incoming NMW, while the most heavily shaded areas highlight shares over 70%. There is significant wage variation across the country. On average, 37% of employees in the country earned below the incoming NMW, varying widely from 22% in the City of Tshwane in Gauteng to 75% in Umzinyathi in Kwa-Zulu-Natal.

One major advantage of this approach is that is captures any spillover effects induced by the NMW hike which occurs within district labour markets. Such effects would be more challenging to identify at the individual-level. Furthermore, this approach is also advantageous in that issues such as measurement error, serial correlation due to temporary shocks, and mean reversion should be less prevalent (Bossler and Schank, 2023). However, a requirement for this approach is that the district-level bite prior to the NMW increase is conditionally exogenous regarding wage changes thereafter. To provide credibility to our approach, we analyse the relative wage distribution below the 2023 NMW to ensure they are similar across districts, as advised by Caliendo et al. (2018) and Bossler and Schank (2023). Finally, this approach also relies on the explicit assumption that no other policies were implemented during the same period that are correlated with the district-level bite. We are not aware of any such policies.

[6] District council identifiers are obtained from StatsSA and we make use of hourly wages, calculated using reported usual weekly hours of work in an individual's main job.

Figure 8. Distribution of the National Minimum Wage bite across district labour markets in South Africa



Authors' own calculations. Source: QLFS 2022Q2 – 2023Q1.
Notes: Sample restricted to working-aged (15-64 years) employees. Estimates weighted using sampling weights and account for the complex survey design. Raw, unimputed wage data provided by StatsSA and are adjusted for outliers and missing data. Bite is calculated as the share of workers in each district in the period prior to the NMW increase who earn below the incoming NMW. The average employment-weighted district-level bite is 0.37, the minimum is 0.22, and the maximum is 0.75 (standard deviation = 0.13).

We use this constructed district-level variable in combination with individual-level data to estimate the impact of the NMW change on wages, employment, and working hours, using Ordinary Least Squares (OLS) regression and a canonical DiD model specification. Our DiD regression relies on variation in the bite interacting with a binary pre/post variable that captures the timing of the NMW increase. In the case of employment, the data for our estimation is aggregated to the district council level and the dependent variable is district-level employment counts on a log scale, while for wages and working hours the data is at the individual-level.[7] We also run an additional DiD specification for wages in which the dependent variable is a re-centered influence function (RIF), also known as unconditional quantile regression, of several distributional statistics of wages. This allows us to examine effects at different points in the wage distribution rather than only at the mean, and it also allows us to produce effects estimates on measures of non-compliance. Throughout this approach, our standard errors are clustered at the district council level, which is the level of variation in the minimum wage bite. For the RIF models, their estimation is based on a block cluster bootstrap with 100 replications.

Formally, our basic individual-level specification is:

[7] An individual-level model for employment probability, where a binary employment dummy variable serves as the dependent variable, is not possible using this specification because both the employed and unemployed would need to remain in the sample. Because wage data are only collected for the employed, only the employed would remain. Hence, we model employment at the district council level and use employment counts on a log scale as the dependent variable. This approach is similarly taken in the referenced empirical literature.

$$y_{it} = \beta_1 + \beta_2 Bite_i + \beta_3 Post_t + \beta_4 Bite_i \times Post_t + \varepsilon_{it} \quad (1)$$

where y_{it} is log of real hourly wages, or weekly working hours, for individual i at time t. $Bite_i$ is the district-specific share of sub-NMW workers prior to the NMW increase, and $Post_t$ is a binary time variable equal to one in the period after the NMW increase and zero prior. The employment model follows a similar specification but as mentioned above, is at the district council level. We include results for an aggregate pre/post model specification in which four quarters of data prior to the NMW increase are included in the 'pre' period and one quarter is in the 'post' period, but we also report results using an event study specification in which the estimates for each wave are shown separately. These event study estimates provide a useful overview of trends in our outcome variables prior to the NMW increase, facilitating the credibility of the DiD approach, and help to examine effect dynamics which highlight the exact timing of any observed effects. Of course, because we only have one 'post' period, such outcome dynamics are not possible to observe at the time of writing given data availability. Finally, as in Bossler and Schank (2023), we include a control for bite-specific linear time trends in a given outcome, however doing so has no effect on our results.

4.2. Approach 2: Panel Data and Individual-level Wage Gap Variation

In our second specification, we take advantage of the panel component of the QLFS, which makes it possible to match individuals across consecutives waves in the survey. In each quarter 75 percent of households are re-sampled, making it possible to follow a subset of individuals for a maximum of four periods before they exit the panel. For our analysis, we construct a panel that includes five waves of data, covering the period 2022Q2-2023Q2. Each individual is observed at least twice – once before the NMW increase and once afterwards. As noted above, all individuals surveyed in March 2023, but not in 2023Q2, are included in the 'post' period. This results in a total employee sample of approximately 31,000 observations over the full period, comprised of 11,827 unique individuals.

Given that we can follow the same individuals over time, it is possible for us to identify all workers that are subject to the 2023 increase and examine what happens to them in the period that follows. However, simply observing these changes in isolation is insufficient to identify NMW impacts. To do so, we need to compare the changes we observe for affected workers in comparison to some suitable sample of workers who are unaffected by the new NMW. We do this in two different ways. First, we focus only on a sample of workers who earn below the incoming NMW and, building on Lee (1999), Dinkelman and Ranchhod (2012), and Ranchhod and Bassier (2017), we create a time-invariant 'wage gap' for each individual in the period prior to the NMW increase. This gap is calculated as the difference between their hourly wage and the incoming minimum wage.

As in the district level approach above, this strategy relies on the assumption that all workers earning below the wage threshold are likely to see their wages rise because of the NMW increase, but that on aggregate, those with wages further below the NMW (a larger 'wage gap') are likely to see their wages rise by more. Indeed, Figure A4 in the appendix reveals a positive correlation between the magnitude of the individual-level wage gap and growth in real hourly wages from before to after the NMW increase. We calculate this wage gap as follows:

$$wage\ gap_i = log(NMW_{2023}) - log(\frac{\sum_{k=2022Q2}^{2023Q1} W_{i,k}}{n}) \quad (2)$$

where $wage\ gap_i$ for individual *i* is the log difference between the incoming NMW and their mean real hourly wage in the period prior to the increase (2022Q2-2023Q1). This returns a positive wage gap value for those earning wages that are below the incoming NMW. Those earning above the incoming NMW are excluded from our sample. We then use the wage gap in a standard DiD regression where the dependent variable is either the log of real hourly wages, a binary employment dummy variable, or the log of weekly hours worked. In the case of employment, we allow for employment status to vary between employed (1) and not employed (0), with the only condition being that everyone must have been employed at some point prior to the 2023 increase, which allows us to calculate a wage gap value. The employment regression therefore picks up changes in overall employment probability, conditional on the pre-increase wage gap. Our formal regression specification is as follows:

$$y_{it} = \beta_1 + \beta_2 wage\ gap_i + \beta_3 Post_t + \beta_4 wage\ gap_i \times Post_t + \gamma_i + \varepsilon_{it} \qquad (3)$$

where y_{it} is either the log of real hourly wages, employment status, or the log of weekly working hours. The wage gap is as defined in (2) above, and our coefficient of interest β_4 is on the interaction term $wage\ gap_i \times Post_t$. We report results with and without controlling for individual fixed effects, γ_i, which account for any observable and unobservable factors which vary between individuals but are constant over time. Throughout this approach, our standard errors are clustered at the individual-level.

4.3. Approach 3: Panel Data and Variation Across Low- Versus High-Wage Workers

In an alternative panel specification, we follow work by Stewart (2004) on the NMW in the United Kingdom and use a treatment and control group to estimate the differential effect of the minimum wage change. The two groups are identified by a wage cutoff that separates 'covered' and 'uncovered' workers, where covered workers are low-wage workers with earnings close to or below the NMW, while uncovered workers are those earning high enough wages to make it unlikely that they would be affected by a change in the NMW. Specifically, we define our low-wage sample as those who earn less than the NMW*1.15, which allows for some spillover effects, and a high-wage sample of workers who earn above this level but not more than NMW*3.5. The resulting real hourly wage bands are low-wage (R0-R29) and high-wage (R29.01-R89). Those earning above R89 per hour are excluded from our sample.

As in the previous estimation strategies, we estimate effects on wages, employment, and hours of work, by testing whether these variables are systematically different between the two groups in the post-law period through the use of a DiD specification. Formally, our specification is set up as follows:

$$y_{it} = \beta_1 + \beta_2 LW_i + \beta_3 Post_t + \beta_4 LW_i \times Post_t + \gamma_i + \varepsilon_{it} \qquad (4)$$

where y_{it} is again the dependent variable which measures either real hourly wages on a log scale, the probability of employment, and weekly working hours on a log scale. The coefficient β_4 on the interaction term measures the difference in outcomes between low-wage and high-wage workers from before to after the NMW was increased. γ_i controls for individual fixed effects. Again, throughout this approach, our standard errors are clustered at the individual-level.

5. Results

We present the DiD results for our cross-sectional and panel estimation strategies below. For the cross-sectional data, our results are based on variation in NMW 'bite' at the district council level, and the output is shown in column (1). This approach uses the full QLFS employee sample over the period under review and includes approximately 60,000 observations in total. For the panel sample, we run two different specifications described above. The first focuses on sub-NMW workers and tests for effects based on a constructed, individual-level wage gap. Results are reported in columns (2) and (3), where the output in column (3) controls for individual fixed effects and is our preferred set of estimates. Finally, our second panel specification compares a group of covered, low-wage workers, against a group of uncovered, higher-wage workers. The sample excludes workers who report earning above R89 per hour in the period prior to the NMW increase, where this is more than 3.5 times the level of the NMW. Results for this approach are shown in columns (4) and (5), and again our preferred estimates are those in column (5) which control for individual fixed effects.

5.1. Wage effects

Our estimates for the effect of the NMW on wages are shown in Table 1, where the coefficient of interest across all columns is 'Treatment x Post'. Together the results from all approaches present strong evidence of a real wage increase in response to the NMW hike, regardless of the worker sample or additional controls added. The coefficient from our cross-sectional, district-level approach is 0.302, and is significant at the 1% level, suggesting a strong and relatively large aggregate effect. Given that we have calculated an average, employment-weighted, district level bite of 0.37, the aggregate wage effect for covered workers in this case is estimated to be 11.2% (0.37*0.302).

In both of our panel specifications we also find significant wage effects. Looking first at the wage gap estimate in column (3), which focuses on a sample of sub-NMW workers, we have a coefficient of 0.325. This means that for a sub-minimum wage worker with the average wage gap (0.65) the result suggests an increase in wages of 21% due to the NMW change (0.65*0.325). To put this into perspective, the average sub-minimum wage worker in our panel sample earns approximately R15 per hour, so this result implies that their wage increased by 21% to R18 per hour. In our second set of panel estimates, which compares low- and high-wage workers, our results suggest that on average, workers in our low-wage treatment group experienced a 19.7% wage increase relative to those in our control group.

Table 1: Effect of the 2023 NMW increase on real hourly wages

	(1)	(2)	(3)	(4)	(5)
Sample:	Cross-sectional	Panel			
Treatment:	(i) District-level bite	(ii) Individual-level wage gap		(iii) Low-wage workers	
Outcome:	Log(real hourly wage)				
Treatment x Post	0.302***	0.289***	0.325***	0.205***	0.197***
	(0.104)	(0.048)	(0.041)	(0.033)	(0.032)
Individual FE	N	N	Y	N	Y
Constant	4.719***	3.403***	3.354***	3.827***	3.764***
	(0.061)	(0.015)	(0.032)	(0.010)	(0.040)
Observations	61 716	14 169	14 169	21 856	21 856

Authors' own calculations. Source: QLFS 2022Q1 – 2023Q2.

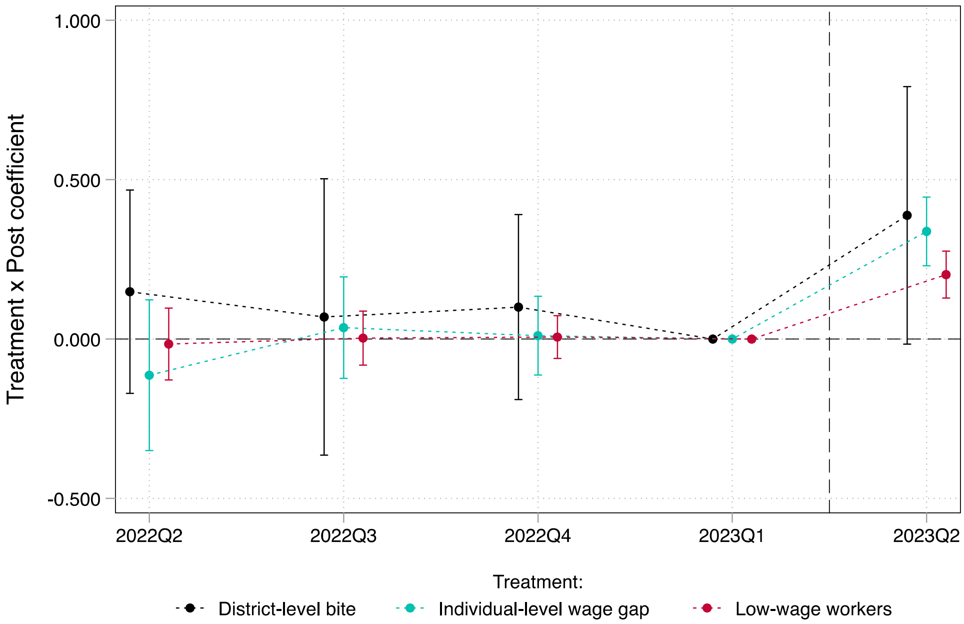
*Notes: Sample restricted to working-aged (15-64 years) employees. Estimates weighted using sampling weights and account for the complex survey design. Raw, unimputed wage data provided by StatsSA and are adjusted for outliers and missing data. Standard errors presented in parentheses and are clustered at the district-level in column (1) and individual-level in columns (2) to (5). Model in column (1) additionally controls for a bite-specific linear time trend. FE = fixed effects. *** p<0.01; ** p<0.05; * p<0.10.*

Taken together, these results present compelling and relatively consistent evidence of wage increases due to the NMW hike that are similar in size. Additional analysis suggests that this aggregate outcome does not differ by gender, youth, or sectoral formaility. However, we do observe marginally larger wage effects for workers in Domestic Work and Agriculture, relative to workers in other sectors.

The results above rely on a two-period time dummy, in which the periods prior to the NMW increase are pooled and compared to the period following the NMW increase. While we have taken care to identify the 'pre' and 'post' periods accurately, an event study design can help to provide additional evidence of the dynamism of effects and support for the parallel trends assumption upon which our DiD analysis relies. Put simply, we conduct the same analysis as reported in Table 1, but use disaggregated, wave-by-wave timing to estimate the effects of the NMW change. These results are shown in Figure 9.

Again, we see a relatively consistent picture of wage effects across all our cross-sectional and panel specifications, and the event study provides a compelling picture of the timing of the observed effects. Prior to the NMW change (2022Q2-2023Q1) our results show no significant changes in the coefficient on our interaction term, and this trend is relatively stable over time. This is consistent with the parallel trends assumption, which implies that in the absence of the NMW hike to follow, this trend would have continued. However, a clear and positive wage effect is evident in the final wave of the period, following the NMW increase. Notably, the effect size is relatively comparable across our different approaches.

Figure 9: Effect of the 2023 NMW increase on real hourly wages, event study design



Authors' own calculations. Source: QLFS 2022Q1 – 2023Q2.
Notes: Sample restricted to working-aged (15-64 years) employees. Estimates weighted using sampling weights and account for the complex survey design. Raw, unimputed wage data provided by StatsSA and are adjusted for outliers and missing data. Standard errors are clustered at the district-level for the district-level bite approach and individual-level for the panel approaches. Spikes represent 95% confidence intervals. Model using the district-level bite approach controls for a bite-specific linear time trend. Panel models control for individual fixed effects.

A final set of wage effect estimates are presented in Table 2, below, where we show how the impact of the 2023 NMW increase on wages differs across the wage distribution. The results are shown using both the cross-sectional approach and both panel specifications. Column (1) reports the aggregate or mean wage effects discussed previously, while columns (2–7) show how these results vary across different wage quantiles, from the 10th to the 60th quantile, in each sample. For the cross-sectional data, which includes the full employee sample, we see wage effects that are larger at the bottom of the wage distribution. These effects decrease in size at higher wage quintiles and lose significance beyond the median of the wage distribution, which is just above R30 per hour. This suggests some degree of wage 'spillover' effects resulting from the 2023 NMW increase, which is not unusual in the international context. The panel results show a similar pattern, but in both specifications the sample is restricted to lower wage workers which affects our interpretation of the impacts across the distribution.

Table 2: Effect of the 2023 NMW increase on real hourly wages across the wage distribution

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS mean	RIF quantile					
		10	20	30	40	50	60

Approach (a): Treatment = district-level bite							
Treatment x Post	0.302***	0.360**	0.261**	0.211***	0.242***	0.206*	0.204
	(0.104)	(0.162)	(0.118)	(0.080)	(0.092)	(0.115)	(0.148)
Constant	4.719***	3.248***	3.779***	3.854***	4.113***	4.630***	5.170***
	(0.061)	(0.101)	(0.058)	(0.039)	(0.054)	(0.097)	(0.108)
Observations	61716	61716	61716	61716	61716	61716	61716
Approach (b): Panel Specification (1) Treatment = individual-level wage gap							
Treatment x Post	0.325***	0.945***	0.484***	0.476***	0.358***	0.240***	0.137***
	(0.041)	(0.118)	(0.047)	(0.040)	(0.036)	(0.030)	(0.028)
Individual FE	Y	Y	Y	Y	Y	Y	Y
Constant	3.354***	3.603***	3.195***	3.272***	3.244***	3.203***	3.177***
	(0.032)	(0.154)	(0.074)	(0.069)	(0.059)	(0.047)	(0.040)
Observations	14169	14169	14169	14169	14169	14169	14169
Approach (b): Panel Specification (2) Treatment = low-wage workers							
Treatment x Post	0.197***	0.188***	0.193***	0.220***	0.242***	0.314***	0.509***
	(0.032)	0.044	0.047	0.034	0.028	0.029	0.033
Individual FE	Y	Y	Y	Y	Y	Y	Y
Constant	3.764***	2.590***	2.973***	3.243***	3.510***	3.746***	4.229***
	(0.040)	(0.093)	(0.065)	(0.056)	(0.041)	(0.044)	(0.056)
Observations	21856	21856	21856	21856	21856	21856	21856

Authors' own calculations. Source: QLFS 2022Q1 – 2023Q2.

*Notes: Sample restricted to working-aged (15-64 years) employees. Raw, unimputed wage data provided by StatsSA and are adjusted for outliers and missing data. Standard errors presented in parentheses and are clustered at the district-level for estimates in approach (a) and the individual-level in approaches (b) and (c). For estimates in columns (2) to (7), standard errors are estimated using a block cluster bootstrap with 100 replications. Models in approach (a) additionally controls for a bite-specific linear time trend. FE = fixed effects. *** p<0.01; ** p<0.05; * p<0.10.*

5.2. Employment effects

Table 3 presents our estimates of the effect of the 2023 NMW increase on employment. In this case, for the cross-sectional approach we include the full sample for one estimate in column (1), and alternatively exclude higher-wage workers to isolate the possible effect on covered workers more directly, in column (2). Regardless of the sample, our district-level estimates do not pick up any changes in employment following the NMW increase.

Regarding the estimates from the panel specifications, shown in columns (3) to (6), the panel sample is restricted to individuals who have been employed in at least one wave prior to the NMW change. This is required for us to generate a wage gap variable and identify low wage workers in each specification. In our wage gap specification, we observe a small negative coefficient, suggestive of some employment declines among sub-NMW workers, where these are larger for those with a higher wage gap.

This translates into an estimated decline of 13,000 jobs attributable to the NMW change. This calculation is based on the coefficient in column (4) and proceeds as follows: A 10% change in the wage gap is associated with a 0.004 percentage point (0.042/10) decrease in employment probability for covered workers, or a 0.45% reduction in employment probability. The average employment probability for sub-NMW workers in the pre-NMW period in our panel sample is 0.88, and we have approximately 2.8 million sub-minimum wage workers in our panel sample in the 'pre' period. Accordingly, a 0.45% reduction in employment is equivalent to a decrease of roughly 13,000 jobs.

Our second panel specification is not significant without fixed effects, as shown in column (5), but becomes larger and statistically significant when they are controlled for. The coefficient suggests that low-wage workers experienced a 3.5% reduction in their employment probability, relative to high-wage workers. This translates into a decrease in employment of around 98,000 jobs, based on the sample of workers included in our panel.

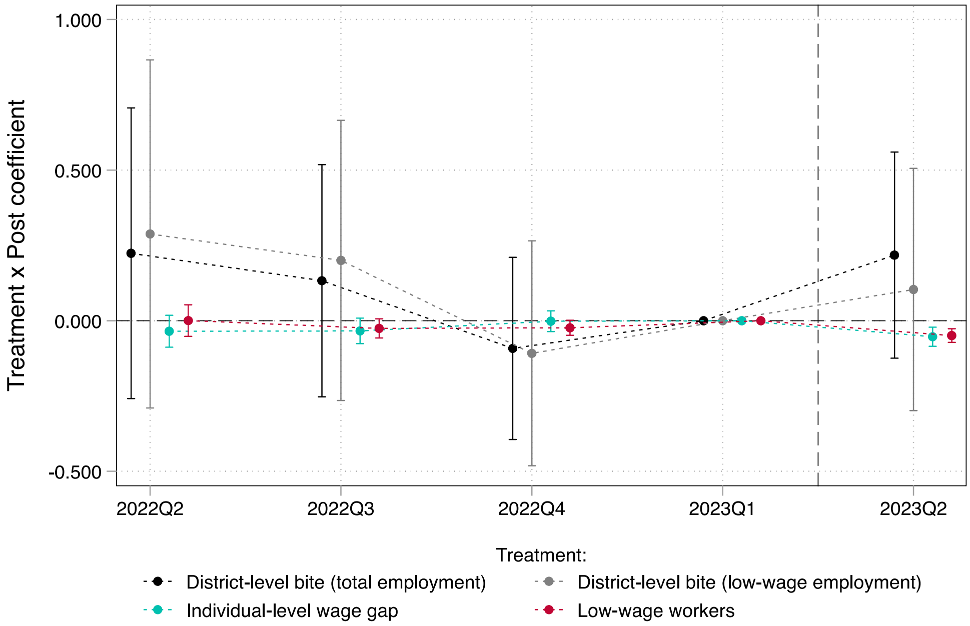
Table 3: Effect of the 2023 NMW increase on employment

	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	Cross-sectional		Panel			
Treatment:	(i) District-level bite		(ii) Individual-level wage gap		(iii) Low-wage workers	
Outcome	Log(employment)		Pr(employment)			
Sub-sample:	Total	Low-wage	Total		Total	
Treatment x Post	0.124	-0.020	-0.048***	-0.042***	-0.006	-0.035***
	(0.148)	(0.158)	(0.015)	(0.013)	(0.011)	(0.010)
Individual FE	N	N	N	Y	N	Y
Constant	14.977***	14.024***	0.893***	0.951***	0.927***	0.879***
	(0.400)	(0.377)	(0.007)	(0.014)	(0.005)	(0.013)
Observations	104	104	16 379	16 379	25 034	25 034

Authors' own calculations. Source: QLFS 2022Q1 – 2023Q2.
*Notes: Sample restricted to working-aged (15-64 years) employees. Estimates weighted using sampling weights and account for the complex survey design. Raw, unimputed wage data provided by StatsSA and are adjusted for outliers and missing data. Standard errors presented in parentheses and are clustered at the district-level in columns (1) and (2) and the individual-level in columns (3) to (6). Model in columns (1) and (2) additionally control for a bite-specific linear time trend. FE = fixed effects. *** p<0.01; ** p<0.05; * p<0.10.*

As in the estimation of wage effects, in Figure 10 we present the same employment estimates shown above but using an event study design – that is, wave-by-wave timing – rather than an aggregate 'pre'/'post' dummy. The estimates remain consistent with those described above for the aggregate case, across both approaches. For the cross-sectional approach, at the district council level we do not find any evidence of employment changes linked to the NMW increase. However, for workers in our panel samples, in both specifications we observe small, negative employment changes that are statistically significant.

Figure 10: Effect of the 2023 NMW increase on employment, event study design



Authors' own calculations. Source: QLFS 2022Q1 – 2023Q2.
Notes: Sample restricted to working-aged (15-64 years) employees. Estimates weighted using sampling weights and account for the complex survey design. Raw, unimputed wage data provided by StatsSA and are adjusted for outliers and missing data. Standard errors are clustered at the district-level for the district-level bite approach and individual-level for the panel approaches. Spikes represent 95% confidence intervals. Model using the district-level bite approach controls for a bite-specific linear time trend. Panel models control for individual fixed effects.

5.3. Working hours effects

Estimates for how working hours were impacted by the NMW increase are shown in Table 4 below. Again, the results include both our cross-sectional and panel sample output, where our preferred estimates are in columns (2), (4), and (6). Overall, the results are mixed but, for the most part, we do not find evidence of significant effects on working hours. This is the case for both specifications in our cross-sectional approach and in our panel specification using the wage gap. However, when we compare our identified group of low-wage workers against a high-wage control group, we find some evidence of a small decrease in working hours. In this case, the estimates suggest that the NMW hike caused a 3.3% greater decrease in hours worked among low-wage workers relative to high-wage workers. For the average low-wage worker in this sample, this translates into a reduction of around 1.4 hours per week.

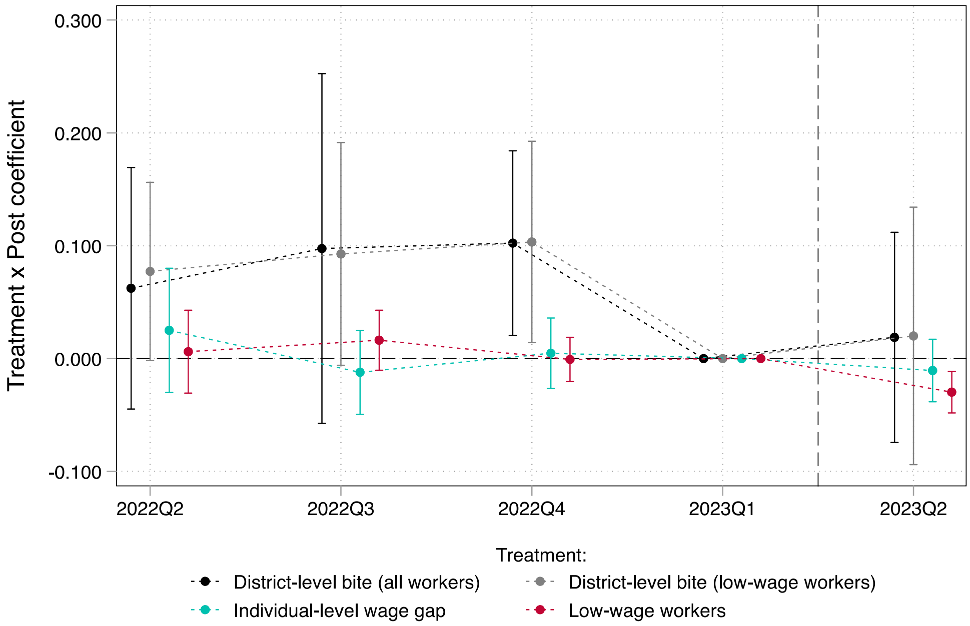
Table 4: Effect of the NMW increase on working hours

	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	Cross-sectional		Panel			
Treatment:	(i) District-level bite		(ii) Individual-level wage gap		(iii) Low-wage workers	
Outcome	Log(weekly working hours)					
Sub-sample:	Total	Low-wage	Total		Total	
Treatment x Post	-0.052	-0.054	-0.025	-0.012	-0.043***	-0.033***
	(0.042)	(0.039)	(0.015)	(0.012)	(0.010)	(0.008)
Individual FE	N	N	N	Y	N	Y
Constant	3.745***	3.820***	3.705***	3.678***	3.680***	3.643***
	(0.017)	(0.021)	(0.008)	(0.021)	(0.006)	(0.020)
Observations	62 290	38 654	14 213	14 213	21 946	21 946

Authors' own calculations. Source: QLFS 2022Q1 – 2023Q2.
*Notes: Sample restricted to working-aged (15-64 years) employees. Estimates weighted using sampling weights and account for the complex survey design. Raw, unimputed wage data provided by StatsSA and are adjusted for outliers and missing data. Standard errors presented in parentheses and are clustered at the district-level in columns (1) and (2) and the individual-level in columns (3) to (6). Model in columns (1) and (2) additionally control for a bite-specific linear time trend. FE = fixed effects. *** p<0.01; ** p<0.05; * p<0.10.*

Looking at the event study estimates in Figure 11 below, we observe similar findings as in the aggregate case above. However, it is also clear that there is some significant variation in working hours prior to the NMW increase using our cross-sectional approach, which threatens the validity of this approach. A small reduction in working hours is evident in our panel wage gap specification, but as in the cross-sectional case, this is not statistically different from zero. It is only in the case where we compare changes in working hours across our low- vs high-wage groups that we observe a small reduction.

Figure 11: Effect of the NMW increase on working hours, event study design



Authors' own calculations. Source: QLFS 2022Q1 – 2023Q2.
Notes: Sample restricted to working-aged (15-64 years) employees. Estimates weighted using sampling weights and account for the complex survey design. Raw, unimputed wage data provided by StatsSA and are adjusted for outliers and missing data. Standard errors are clustered at the district-level for the district-level bite approach and individual-level for the panel approaches. Spikes represent 95% confidence intervals. Model using the district-level bite approach controls for a bite-specific linear time trend. Panel models control for individual fixed effects.

5.4. Non-compliance

Our estimates for the effect of the NMW increase on measures of non-compliance are shown in Table 5, where the coefficient of interest across all columns is again 'Treatment x Post'. Given that estimates of non-compliance rely on data from the entire wage distribution, we only present effect estimates resulting from our district-level bite approach, as opposed to the panel data approaches which use samples restricted towards lower-wage workers. As before, we present results for two sets of non-compliance measures: one using the 2023 NMW threshold, and another using the more conservative threshold which allows for a 10% lower threshold. Together, and regardless of the threshold used, the results suggest that the 2023 NMW increase had a significant, negative effect on minimum wage non-compliance. In other words, the hike appears to have improved compliance, despite a higher NMW level.

The coefficients in columns (1) and (2) of approximately 0.12, both significant at the 1% level, combined with the average, employment-weighted, district-level bite of 0.37, suggest that the 2023 hike in the NMW reduced the non-compliance headcount ratio – the share of workers earning below the NMW – by between 4.4% (0.37*0.118) and 4.5% (0.37*0.121).

In addition to shifting workers up from below to above the NMW threshold, the hike appears to have reduced to the average distance from the NMW for sub-minimum wage workers (depth). The estimates in columns (3) and (4) suggest that hike reduced non-compliance depth by between 1% (0.028*0.37) and 1.2% (0.032*0.37). It is notable that the hike had a much larger effect on non-compliance headcount than depth – by a factor of approximately four. These varied but complementary effects are consistent with the wage effects estimated across the wage distribution, shown in Table 2.

Table 5: Effect of the 2023 NMW increase on non-compliance

	(1)	(2)	(3)	(4)
Non-compliance measure:	Headcount: FGT(0)		Depth: FGT(1)	
Threshold:	NMW	NMW-10%	NMW	NMW-10%
Approach: Treatment = district-level bite				
Treatment x Post	-0.118***	-0.121***	-0.032**	-0.028**
	(0.041)	(0.041)	(0.014)	(0.013)
Constant	-0.040*	-0.082***	-0.035***	-0.034***
	(0.021)	(0.021)	(0.006)	(0.006)
Observations	61716	61716	61716	61716

Authors' own calculations. Source: QLFS 2022Q1 – 2023Q2.
*Notes: Sample restricted to working-aged (15-64 years) employees. Raw, unimputed wage data provided by StatsSA and are adjusted for outliers and missing data. Standard errors presented in parentheses and are clustered at the district-level and are estimated using a block cluster bootstrap with 100 replications. All models additionally control for a bite-specific linear time trend. *** p<0.01; ** p<0.05; * p<0.10.*

6. Conclusion

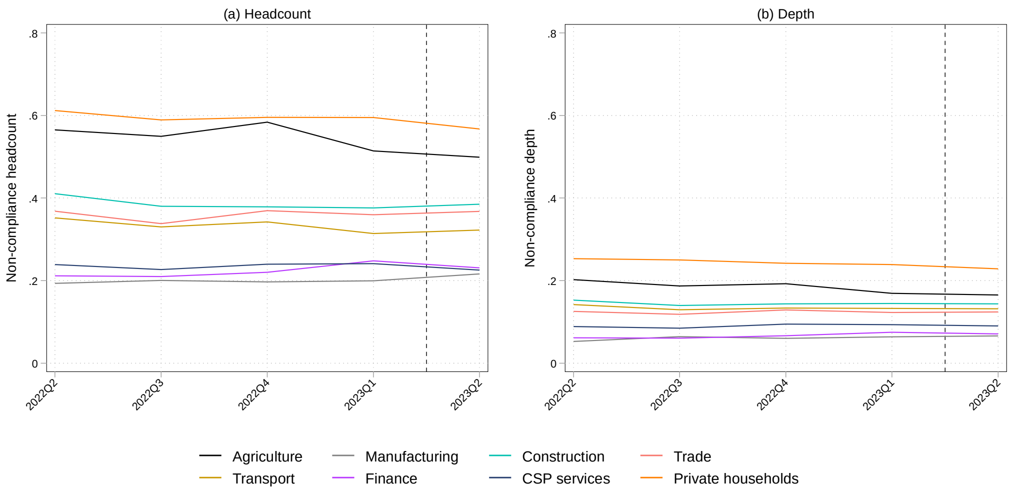
Changes to the National Minimum Wage (NMW) in South Africa in 2023 took place in a context of low economic growth and relatively high inflation. The 2023 increase was larger than previous annual increases, raising the wage floor by 9.6% in nominal terms and 2.5% in real terms. The hourly NMW increased from R23.19 to R25.42, affecting roughly 37% of employees in the labour market. Descriptive labour market trends do not reveal an obvious series of adjustments following the NMW increase; however, there is a noticeable spike in the wage distribution in 2023Q2 occurring around the level of the new NMW, which is suggestive of a causal effect. Nevertheless, a more thorough analysis is required to isolate this effect. By making use of individual-level, cross-sectional and panel labour force survey data and a combination of analytical approaches, this report provides an empirical analysis of the short-term effects of this increase on wages, employment, working hours, and non-compliance.

Our first approach builds on work by Bossler and Schank (2023) and exploits variation in the share of sub-NMW workers at the district council level (a measure of 'bite') to identify the effects of the NMW change. Our second and third approaches makes use of a sub-sample of unique individuals who can be identified both before and after the NMW increase, with the former using an individual-level wage gap approach (as an alternative measure of 'bite') and the latter using a low- vs high-wage worker comparison.

Overall, our results suggest that the 2023 NMW hike had a strong and positive effect on real hourly wages, a finding which is consistent across approaches and robust to changes in model specification. Across different samples, we find that the NMW change led to an estimated increase in real hourly wages of between 11% and 21% on average. Larger wage effects are observed towards the bottom of the distribution. Consistent with these effects, we find that the higher NMW reduced non-compliance headcount by 4% and depth by 1%, representing small but still statistically significant effects. Our results with respect to employment and working hours effects are both mixed. No aggregate employment effects are found when using the full cross-sectional dataset and district-level bite approach, but by contrast, small and negative employment effects are estimated when using the restricted panel samples. The findings for working hours are similarly equivocal. This suggests that the strong wage increases induced by the NMW hike may have been partially offset by reductions in employment and working hours, but only marginally so.

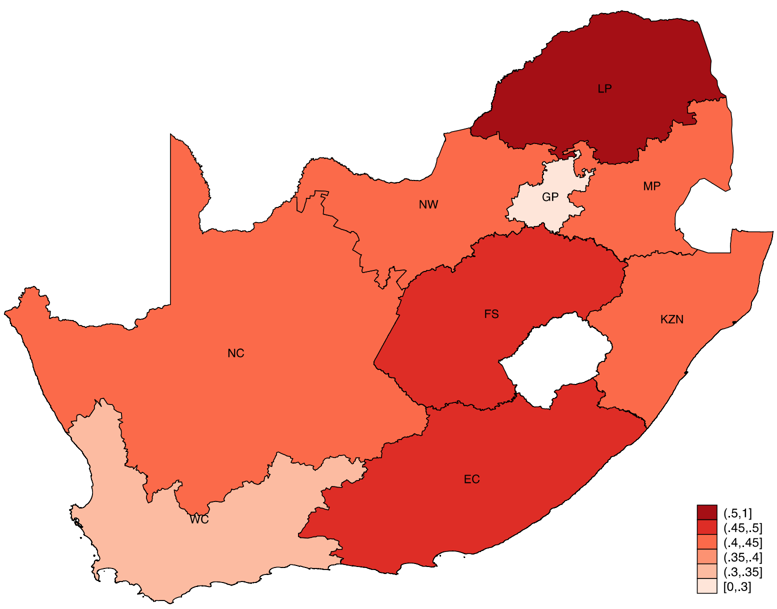
7. Appendix

Figure A1: Trends in National Minimum Wage non-compliance by industry, 2022Q2 – 2023Q2



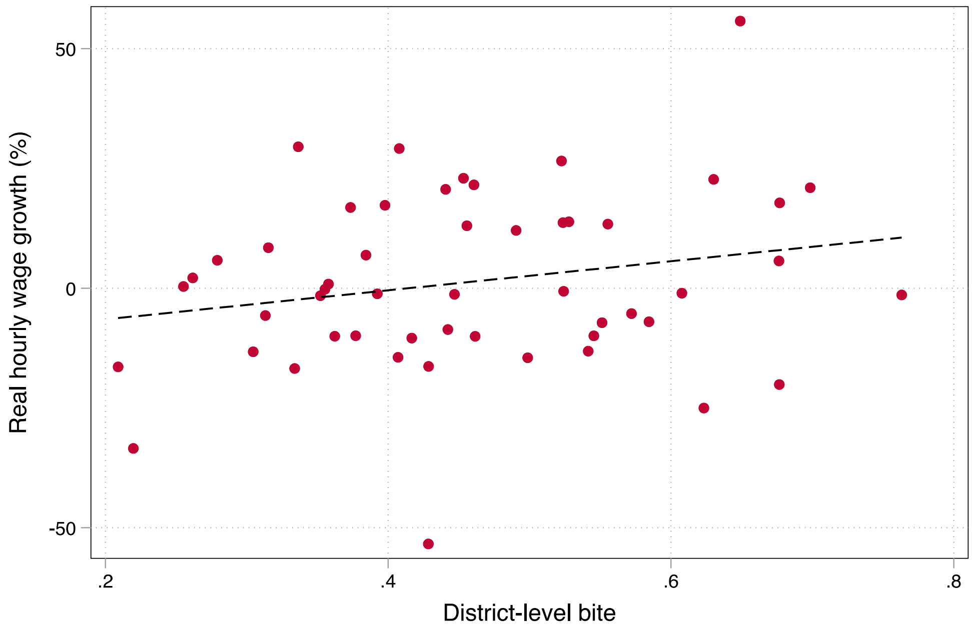
Authors' own calculations. Source: QLFS 2022Q2 – 2023Q2.
Notes: Sample restricted to working-aged (15-64 years) employees. Estimates weighted using sampling weights and account for the complex survey design. Raw, unimputed wage data provided by StatsSA and are adjusted for outliers and missing data. Shaded areas represented 95% confidence intervals. Vertical line distinguishes the periods before and after the 2023 NMW increase.

Figure A2: Distribution of the National Minimum Wage bite across provincial labour markets in South Africa



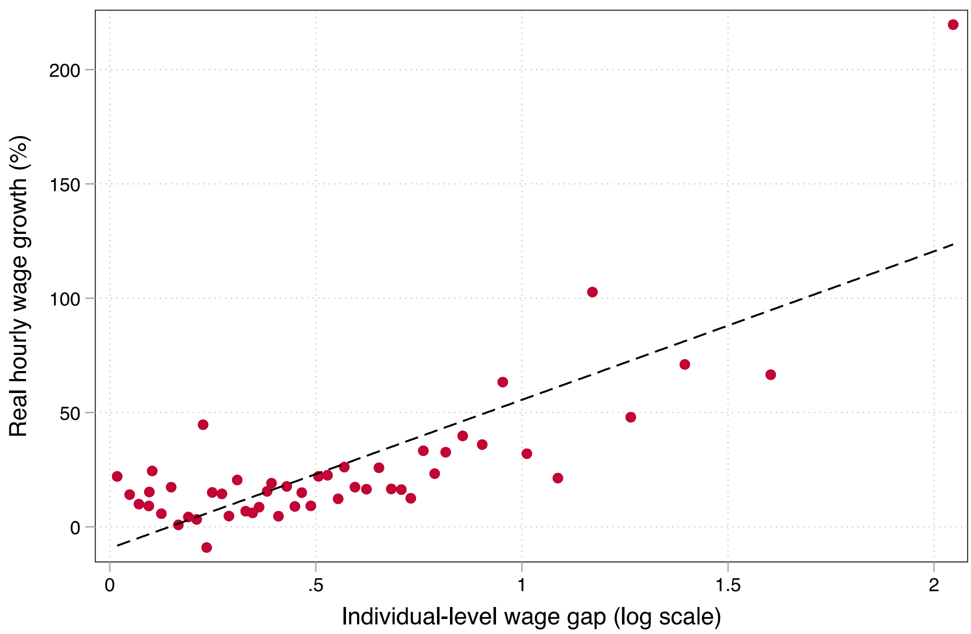
Authors' own calculations. Source: QLFS 2022Q2 – 2023Q1.
Notes: Sample restricted to working-aged (15-64 years) employees. Estimates weighted using sampling weights and account for the complex survey design. Raw, unimputed wage data provided by StatsSA and are adjusted for outliers and missing data. Bite is calculated as the share of workers in each province in the period prior to the NMW increase who earn below the incoming NMW. The average employment-weighted provincial-level bite is 0.37, the minimum is 0.27, and the maximum is 0.51 (standard deviation = 0.09).

Figure A3: Scatterplot of district-level real wage growth and National Minimum Wage bite



Authors' own calculations. Source: QLFS 2022Q2 – 2023Q2.
Notes: Sample restricted to working-aged (15-64 years) employees. Estimates weighted using sampling weights and account for the complex survey design. Raw, unimputed wage data provided by StatsSA and are adjusted for outliers and missing data.

Figure A4: Binned scatterplot of individual-level real wage growth and National Minimum Wage gaps



Authors' own calculations. Source: QLFS 2022Q2 – 2023Q1.
Notes: Sample restricted to working-aged (15-64 years) employees. Estimates weighted using sampling weights and account for the complex survey design. Raw, unimputed wage data provided by StatsSA and are adjusted for outliers and missing data.

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