Minimum wages and unemployment during economic shocks*

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Abstract

This paper studies how the imposition of a minimum wage can affect how labour markets respond to economic shocks. Using data from South Africa, we show that an agricultural minimum wage leads to higher mean wages with no significant impacts on mean employment. However, these positive aggregate outcomes hide important heterogeneity: the imposition of the minimum wage leads to substantial declines in employment in the sector in the wake of negative weather-related economic shocks, which typically exert downward pressure on wages. The increased variation of employment across years in the post-law period suggests caution in interpreting the overall welfare impacts of minimum wage laws.

Keywords: minimum wage, agriculture, shocks, weather, South Africa
JEL Codes: J13, J38, J43, O12, O13

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1 Introduction

Effects of minimum wages on employment are hotly debated. Basic theory suggests that raising wages should cause involuntary unemployment but, on average, studies from the US and other industrialised countries have found only small disemployment effects (Card and Krueger, 2016). There is growing interest in developing countries – where enforcement is often lax or selective, labour markets can differ markedly from developed countries and instituted wage increases may be larger (Neumark et al., 2007; Lemos, 2009) – but outcomes have been mixed.

Surprisingly absent from the minimum wage literature has been any examination of how employment effects may differ over time depending on economic conditions. The minimum wage literature has focused on aggregate employment (e.g. Meer and West, 2016) or the distributional effects on different types of workers (e.g. Cengiz et al., 2019; Jardim et al., 2022). However, even if a minimum wage has a limited impact on overall or group employment, it could affect how labour markets respond to economic shocks. By making the wage bill less affordable for employers and/or reducing the flexibility of employers to adjust wages to shocks (Franklin and Labonne, 2019), the minimum wage could increase the elasticity of employment to negative shocks.

This issue is particularly relevant in low and middle-income countries, where typically a large share of the labour force works in agriculture and is, therefore, especially vulnerable to annual weather shocks. With climate change increasing the frequency of these shocks, numerous studies have sought to measure their impacts on labour markets (Townsend, 1994; Jayachandran, 2006; Henderson et al., 2017; Jessoe et al., 2018). In this paper, we bring together these two strands of literature and explore how the introduction of an agriculture minimum wage law in South Africa affects how labour markets adjust to weather-related economic shocks, leading to important, previously undocumented, heterogeneity.

Agriculture has historically accounted for a substantial share of employment of low-skilled workers in South Africa. However, there has been a trend towards commercialisation and mechanisation, and in the three decades between 1980 and 2010, over one million agricultural jobs were shed (Liebenberg and Johann, 2013). Agricultural employment is also highly variable due to currency and, in particular, weather fluctuations (BFAP, 2016). There is anecdotal and descriptive evidence of droughts causing massive destruction in the agricultural economy (Vogel and Drummond, 1993; BFAP, 2016). With climate change becoming an increasingly worrying part of everyday life, weather shocks may play even larger role in the future.

In 2003, the South African government implemented a national agricultural minimum wage. This was set at the 70$^{\text{th}}$ percentile of the prevailing wage distribution, leading to a substantial increase in the median wage. In the single published national study, Bhorat et al. (2014) find evidence of a positive effect of the law on the income of agricultural workers but a negative effect on their employment (with no significant effect on hours worked). However, a few smaller-scale studies papers surveying farm owners and/or workers in regional agricultural sub-industries found more modest or no disemployment effects (Conradie, 2003; Murray and Van Walbeek, 2007; Naidoo, 2019).

While our main focus is on the impacts of the interaction between the law and economic shocks, we first reanalyse the main effects of the law, improving the matching of minimum wage levels to district boundaries. Using large, nationally representative labour surveys from September 2001 to September 2007, our empirical strategy involves changes over time across district councils that are differentially affected by the new minimum wage law. Specifically, we create a variable that measures the difference between the new minimum wage law and prevailing agricultural wages in a given district council, similar to previous work on minimum wages (e.g. Lee, 1999; Dinkelman and Ranchhod, 2012; Bhorat et al., 2014).

The minimum wage was announced in December of 2002 and took effect just months later, leaving little time for employers and employees to react in advance of the change.

Using the repeated cross-sectional surveys, we present additional evidence that this wage gap variable does not predict changes prior to the implementation of the minimum wage. We also demonstrate that the impacts of the law on employment and agricultural wages are immediate and are constant across the four years following implementation. In other words, if trends or confounders are responsible for the effects, it would have to be the case that they acted immediately upon implementation of the law and then not again for the remainder of our sample period.

Guided by a simple model of labour allocation, we first show that the minimum wage had large effects on prevailing agricultural wages in South Africa. A one-standard-deviation increase in the wage gap is correlated with an increase in the prevailing (agricultural) wage of around 9 percent following implementation of the minimum wage law. Importantly, we find no disemployment effects in the agricultural sector; in fact, while overall employment does not respond to the wage gap measure, hours in agriculture actually increase by around 3-4 hours per month. The overall wage increase is approximately equal for men and women, but the former see a noticeable uptick in overall hours while the latter do not, leading to a larger increase in monthly agricultural income for men relative to women.

Our main set of results explores how the agricultural minimum wage law affects the ability of the labour market to adjust following shocks. We show that average effects on wages and employment can hide important changes related to agricultural productivity levels, proxied by rainfall.

Following Jayachandran (2006), we define a productivity shock variable based on historical rainfall patterns. We then show that the effect of the minimum wage differs substantially (and significantly) depending on agricultural productivity levels. Specifically, during normal years, we see increases in agricultural hours and the agricultural wage for those who are employed in agricultural wage employment. However, we see a noticeable relative decrease in agricultural hours during bad years and a symmetric increase during good years. For women, we see the largest effects for those in agricultural wage employment; when we expand the sample to all sectors, effects attenuate substantially. For men, on the other hand, this increase in the variance carries over to the entire population. When we impute income for those self-employed in agriculture, we find a consistent pattern among all adults: significant negative effects on total agricultural income for men but not women during bad years and increases for both during good years.

Our final set of results looks at whether employment in non-agricultural sectors changes in response to the shocks we see in the agricultural sector. We look at overall employment and examine whether it responds in the opposite direction of overall agricultural employment. Looking across all adults, we see evidence that female non-agricultural employment responds in such a way. These results are not significant, however, so we are only able to conclude that it does not seem to respond overall. For men, however, we see total employment effects in the same direction as agricultural employment. The magnitude of these effects is roughly equal to that for agricultural employment, indicating that men are not able to reallocate labour to offset any of the reduction in agricultural employment.

We contribute to several strands of literature. First and foremost, we contribute to the literature on labour market policy and local economic shocks. Adhvaryu et al. (2013) and Chaurey (2015) examine employment responses to local demand shocks using state-level variation in firing costs in India. Colmer (2021) uses the same variation in labour regulations to test the extent to which labour reallocation mitigates the consequences of temperature-driven reductions in the demand for agricultural labour. Santangelo (2019) examines whether the introduction of a large-scale rural workfare programme affects the response of local economies to agricultural productivity shocks. Kaur (2019) finds that nominal wage rigidities prevent labour markets from clearing after economic shocks, resulting in increased unemployment. No papers have, however, focused on the influence of minimum wage legislation on the effects of productivity shocks.

While some consider minimum wages as an important welfare policy (Eyraud and Saget, 2008), we show that this type of policy can also lead to larger variations in employment. When employment is seasonal (Breza et al., 2021) and when households have limited liquidity, as is often the case in developing countries (Casaburi and Willis, 2018; Fink et al., 2020), households may not be able to fully cope with variability. We have ample evidence that seasonal hunger is a prevalent condition in developing countries with long-term impacts (e.g. Christian and Dillon, 2018; Dostie et al., 2002). Our results suggest caution in interpreting average effects of minimum wages in such conditions, as increased variability can lead to reduced welfare (Ravallion, 1988), especially for the poor, for whom unexpected shocks and variance are an important part of life (Merfeld and Morduch, 2022).

We also add to the relatively small literature on the effects of minimum wages in developing countries (e.g. Neumark et al., 2006; Gindling and Terrell, 2007; Dinkelman and Ranchhod, 2012; Bhorat et al., 2014). While some previous research in developing country settings has found small or null effects of minimum wages (Badaoui and Walsh, 2022; Dinkelman and Ranchhod, 2012), other papers have found sizeable disemployment effects either on the labour force as a whole (Gindling and Terrell, 2007) or on specific subgroups of the population, like women (Feliciano, 1998; Arango-Arango, 2004). Our paper highlights an unexplored and important channel for minimum wage laws having an impact on employment in developing countries.

2 A simple model of labour allocation

In this section, we present a simple model of labour allocation in agriculture. Most of the model comes directly from Jayachandran (2006), with a few changes. Most notably, we abstract away from financial markets, without loss of generality with respect to our main result, and discuss the addition of a minimum wage. In an agricultural economy, there are N agents, each of whom has time endowment $\bar{h}$ (which does not vary across agents). Agents derive utility from leisure, l_i, and consumption, c_{it}, across two time periods, $t = \{1, 2\}$.

In the first period, agents allocate time between leisure and labour, h_i, while in the second period income is exogenous, leading to no labour/leisure choice, so we suppress subscripts for these variables.[1] We assume Stone-Geary preferences over consumption and leisure:

$$u(c_{it}, l_i) = \log(c_{it} - \underline{c}) + \frac{1-\alpha}{\alpha} \log l_i, \tag{1}$$

where $\alpha \in (0, 1)$. We assume utility is additive and separable across the two periods, with a discount factor of b. We also assume that agents can save income from period one to consume in period two, but they do not receive interest and they are not able to borrow.

Agents are also endowed with land, k_i, with $\sum_i k_i = K$. Agents can hire in labour to work on their land and agricultural production follows a Cobb-Douglas technology,

$$f(d_i, k_i) = \gamma d_i^{\beta} k_i^{1-\beta}, \tag{2}$$

where d_i is the amount of labour applied to land, k_i, and $\beta \in (0, 1)$. γ is a stochastic productivity shock which takes on two possible values, γ_L and γ_H, each with probability 0.5 and $\gamma_H > \gamma_L$.

Putting these together, the agent's problem is

$$\max_{c_{it}, l_i, d_i} \log(c_{i1} - \underline{c}) + \frac{1-\alpha}{\alpha} \log l_i + b \log(c_{i2} - \underline{c}) \tag{3}$$

[1]Since leisure in the second period enters as a constant, we also suppress second-period leisure to make presentation clearer.

subject to

$$c_{i2} = \gamma d_i^{\beta} k_i^{1-\beta} - d_i + w(\bar{h} - l_i) - ci1 + y_i, \tag{4}$$

where Equation 4 imposes that the agent spend all remaining money in period 2.

All landholders maximise on-farm profits by setting the returns to hiring equal to the wage rate:

$$\frac{\partial f}{\partial d_i} = \beta\gamma \left(\frac{k_i}{d_i}\right)^{1-\beta} = w. \tag{5}$$

Rearranging, we can write optimal labour demand as

$$d_i^* = k_i \left(\frac{\gamma\beta}{w}\right)^{\frac{1}{1-\beta}}. \tag{6}$$

As Jayachandran (2006) shows, optimal labour supply equals

$$h_i^* = \frac{1-\alpha}{1+\alpha b}\left[\frac{\alpha(1-b)}{1-\alpha}\bar{h} - \frac{y - 2\underline{c}}{w} - \frac{1-\beta}{w}\left(\frac{\gamma^{\beta}}{w^{\beta}}\right)^{\frac{1}{1-\beta}} k_i\right]. \tag{7}$$

2.1 Imposing a minimum wage

The wage rate is determined endogenously, with the equilibrium wage being the wage, w^*, that equalises labour demand and labour supply:

$$\sum_{i=1}^{N} h_i^*(w^*) = \sum_{i=1}^{N} d_i^*(w^*). \tag{8}$$

The equilibrium wage, w^*, is increasing in agricultural productivity, or $w^*(\gamma_H) > w^*(\gamma_L)$. Consider the imposition of a minimum wage, $\underline{\text{w}}$, which acts as a wage floor and prevents w^* from falling below $\underline{\text{w}}$.

For simplicity, assume that $w^*(\gamma_H) > \underline{w}$.[2] In this case, the imposition of the wage floor has no effect on equilibrium values $d_i^*(\gamma_H)$ and $h_i^*(\gamma_H)$. Now consider negative productivity shocks, where $w^*(\gamma_L) < \underline{w}$. In this case, the minimum wage will prevent the equilibrium wage from falling to equalise labour demand and labour supply, leading to a labour surplus. Moreover, the size of this new labour surplus is increasing in the difference between the minimum wage and the optimal equilibrium wage, since $\frac{\partial d_i^*}{\partial w} < 0$ and $\frac{\partial h_i^*}{\partial w} > 0$. However, we do not observe desired labour supply, but only actual hiring, which equals d_i^*. Nonetheless, the same predictions hold when just looking at d_i^* since the derivative is negative. This is the core prediction we aim to test in this paper.

3 Context

3.1 The agricultural sector

For more than three centuries, government policy favoured White commercial farmers at the expense of Black farmers, sharecroppers and farm workers (Van Onselen 1991; Pahle 2015). After the National Party came to power in 1948, decades of racially discriminatory legislation such as the 'colour bar', and an education system that invested heavily in White skills accumulation while reproducing an unskilled or semi-skilled Black workforce, created a highly distorted labour market and one of the world's most unequal societies (Lipton 1986; Terreblanche 2002). Whites controlled most of South Africa's land and capital, while rural Africans and Coloureds who had been systematically dispossessed of their land were either confined to under-resourced 'homelands' or employed as low-paid farm workers on heavily subsidised White-owned commercial farms (Hall Cousins 2018).

After the transition to a democratic dispensation in 1994, progressive legislation was introduced that conferred economic, social, cultural, civil and political rights to all South

[2] To generate the comparative statics below, we only require that $w^*(\gamma_H) > w^*(\gamma_L)$. We make the assumption here regarding the minimum wage just to simplify the exposition in this paragraph.

Africans, including labour laws that regulated the relationship between employers and employees and aimed to protect workers against unfair labour practices.

Historically many agricultural workers lived on the farms where they were employed with their extended families. Feudal relationships, conditions terrible.

As in many other developing countries, until the 1990s industrial agriculture in South Africa was heavily subsidised and protected.

At the same time, some subsistence farming continues to take place, mostly notably in former Apartheid homelands ('Bantustans').

"feudal relationships between farmers and farm workers are increasingly breaking down through movement off farms (for various reasons, including, but not only, evictions) and a shift away from the use of permanent workers towards the use of indirect labour and short-term employment contracts" (2015:1)

After the end of Apartheid, the government quickly deregulated and liberalised the sector. Over the last 30 years, a substantial share of smallholder farms in the commercial sector have consolidated into larger farms, many of which are oriented towards the export market.

Trade liberalisation has also deepened South African producers' integration into global food value chains. It has done so at a point in time when international (and local) retail power has become increasingly consolidated and more powerful. The combined processes of market deregulation and supermarket consolidation have served to weaken producers' collective bargaining power in the market place. As a result, some of the agricultural value chains, which were previously controlled by South African producers, are now controlled by international retailers. In the process, most South African producers have become price takers (Visser and Ferrer, 2015)

(Ferrer and Visser 2015; Bahsier 2017). Trade liberalisation and deregulation has considerably weakened producers' collective power over the last decade. The result has been that they have become price takers and are increasingly on the defensive to protect their dwindling profit margins

Despite the agriculture sector's relatively small contribution to GDP - it contributed only 2.33-3.88% of annual GDP between 2001 and 2007 (World Bank, 2020) - and the fact that industrialisation of the sector has resulted in a downward trend in agricultural employment, the sector still employs a substantial number of mostly low-skilled workers.[3] During our period of study, 2001-2007, just over one million people were employed in the agricultural sector as their primary activity (accounting for approximately 6% of the labour force), the vast majority of whom had not completed high school. However, the sector also indirectly benefits or involves a wider group of people. According to the 2011 Census, in addition to workers who counted agriculture as their primary activity, an additional one million people were casually involved in agriculture at the time of the census (Liebenberg and Johann, 2013). Furthermore, a large number of jobs are created in industries with backward and forward linkages to the sector.

3.2 The 2003 agricultural minimum wage

The agricultural minimum wage was officially introduced in March 2003. Until this time the agricultural sector had been barely unionised and reported the lowest wages of any sector in the country (Bhorat et al., 2014). In addition to setting a legal wage floor, the new law also defined conditions of employment for the agriculture sector that included maximum working hours and the establishment of a written employment contract for employees. According to Sectoral Determination No. 75 of 1997, the law was to apply to 'the employment of farmworkers in all farming activities in South Africa'. The law was intentionally vague about what was entailed by 'farming activities': the exact wording was: "Without limiting its meaning, 'farming activities' includes primary and secondary agriculture, mixed farming, horticulture, aqua farming and the farming of animal products

[3]During our period of study, 2001-2007, agricultural workers represented approximately 19% of the workforce with fewer than ten years of education.

or field crops excluding the Forestry Sector."

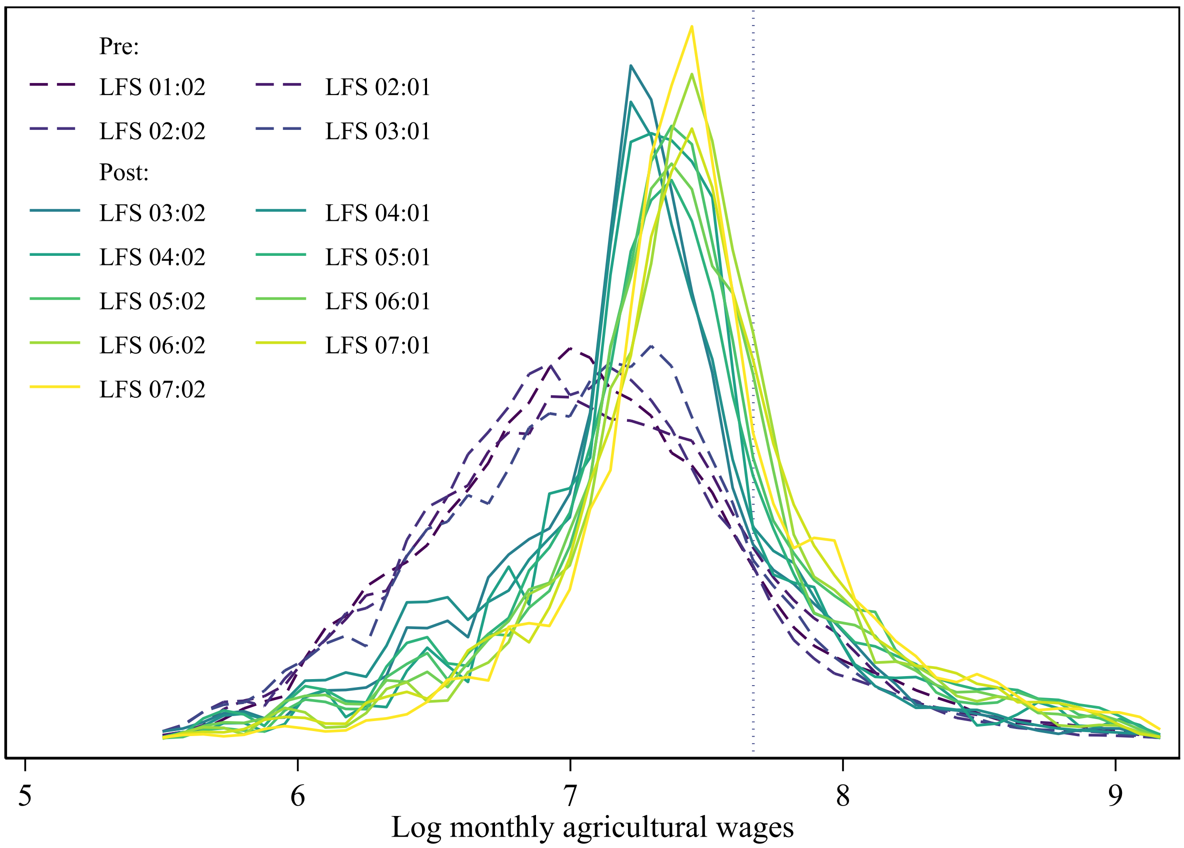
Importantly, the minimum wage set for the agriculture industry in South Africa resulted in changes to low-skilled worker wages that are several times greater those brought about by minimum wages in developed country contexts. The median district experienced a 43% increase in agricultural monthly wages for full-time workers after the minimum wage was implemented.

A higher minimum wage was applicable in more urbanised local municipalities - classified as Area A municipalities - while a lower minimum wage applied to more rural municipalities - classified as Area B municipalities. Labour market data prior to September 2003 (described below) do not contain any information regarding the local municipality of residence of participants; however it is possible to work out the district council (a larger administrative unit) of residence from the unique identification numbers. Most district councils overlap with only Area A or Area B municipalities; where they overlap with local municipalities of both categories, we assign a minimum wage level depending on the relative proportions in terms of land area.

In 2003, over 80% of farm workers were earning less than the urban minimum, and over 60% were earning less than the rural minimum (Bhorat et al., 2014). To support implementation of the new legislation, labour inspectors were tasked with enforcement activities, visiting farms, reviewing worker contracts and interviewing a sample of workers. However, the fact that some farms were very remote made this task quite difficult. Still, a qualitative study, while no means representative, found a fairly high rate of compliance in terms of granting of key rights. Most producers in this study complied with minimum wage legislation. ADD

It is easy to see the increase in wages in Figure 1, which shows kernel density plots of (hourly) agricultural wages in each wave of the survey. The four dashed density estimates are wages before the implementation of the minimum wage law; they are relatively tightly bunched together, with overlap across the range of the distributions. The other densities

Figure 1: Minimum wage and agricultural wages



Notes: The four dashed lines are from survey waves prior to the implementation of the minimum wage. Lighter lines indicate later waves, with LFS 03:02 referring to the very first wave following implementation of the new wage floor.

show that the wage distribution changed substantially upon implementation of the law. The average and mode increased, though not quite to the level of the minimum wage (the dotted vertical line). Also noteworthy is that the wage distribution for agricultural (wage) workers appears more compressed following the imposition of a wage floor, which is consistent with some previous evidence on minimum wages in developing countries (Gindling and Terrell, 1995; Lemos, 2009).

4 Data and empirical strategy

4.1 Labour market data

The labour market data for this study come from 13 waves of the South African Labour Force Survey (LFS) conducted between September 2001 and September 2007. These LFS surveys are biannual rotating panel surveys, conducted in February/March and September each year and include detailed data on work and unemployment experiences of 60,000 to 70,000 working-age individuals living in 30,000 households. In each wave, 20% of households interviewed in the previous wave are rotated out of the survey entirely.[4] The chosen sample includes four waves prior to and including the legislation's effective date (March 2003) and nine afterwards. While there are three earlier waves of data going back to March 2000, the baseline sample was redrawn for the September 2001 round and so we start the analysis with data from this round, following Dinkelman and Ranchhod (2012). We treat all 13 waves as repeated cross sections over time.

The sample of workers includes all urban and rural employed and unemployed men and women aged 18 to 64. We identify agricultural workers in each wave of the LFS using the the South African Standard Classification of Occupations (SASCO) codes, as well as the three-digit International Standard Industrial Classification (ISIC) industry codes. The LFS contains information on wages and hours worked, which allows us to construct data on wages, total income, and hours. There is very little income information for self-employed workers. In the analysis with these workers, we impute income in different ways, a topic to which we return below in the results section.

The labour force surveys give geographic information only for provinces, of which there are nine in the country. It is possible to work out magisterial districts (an administrative

[4]There is a panel data component of the LFS survey, but this is not well maintained (and also not made publicly available) and, following others, we choose not to use it because of serious concerns about the representativeness and quality of the panel data set of workers (cf. Dinkelman and Ranchhod (2012) for a longer discussion).

layer) for the period September 2001 to January 2003 based on the unique identification codes for respondents. However, for the period September 2003 to September 2007, the unique identification codes give information only about local municipalities, which were not defined in the earlier period. District municipalities were constant over the period of study and both magisterial districts and local municipalities fit neatly into district councils. These are therefore used as our geographic units of analysis is this paper.[5]

4.2 Baseline estimation

In order to identify the effects of the minimum wage increase, we create a new variable that measures the difference between pre-law agricultural wages and the post-law official minimum wage. While there is a time component to the law, there is also substantial geographic diversity in the law's "bite"; areas with wages further below the new floor face larger effects from the wage change. This variable identifies the cross-sectional variation in the wage gap between district councils in the pre-law period. Following Lee (1999) and similarly to Dinkelman and Ranchhod (2012) and Bhorat et al. (2014), we define the district-level wage gap as:

$$WG = log[min(W_{d}*)] - log[median(W'_{d})], \tag{9}$$

where $log[min(W_{d}*)]$ is the new minimum wage and $log[median(W'_{d})]$ is the median prevailing agricultural wage in a given district. With this wage-gap variable, we are able to analyse the heterogeneous effects of the new law in combination with the temporal component of the data.

[5]While it is possible that some of the larger district councils could be seen as including more than one local labour market, district councils have been used as the geographic unit of analysis in several well-published papers (e.g. Bhorat et al., 2014) and it is even quite common for papers to use provincial units, which is the highest administrative layer in the country (e.g. Magruder, 2010; Dinkelman and Ranchhod, 2012). For this particular analysis, larger geographic units may be preferable since the effects of weather shocks may not be captured at high resolutions because rainfall in a limited area may not have enough of an impact on local labour market outcomes when there is smoothing across agricultural markets (Harari and Ferrara, 2018).

Based on a review of the Department of Labour documentation on setting the agricultural minimum wage, it appears that the potential impact of the wage on employment had minimal if any role in the policy decision. For example, in DoL (2001) it states that "...a minimum wage cannot be opposed purely on grounds of its adverse effect on employment" (cited in Garbers et al., 2015). This gives credence to the assumption that the size of the wage gaps used in this study are not correlated with trends in employment or wages. Figure 2 shows the distribution of this "wage gap" variable across the country. Wages were highest in the Cape region (far southwest) and closer to the large cities (e.g. Pretoria/Johannesburg in the middle of the country and Durban to the southeast).

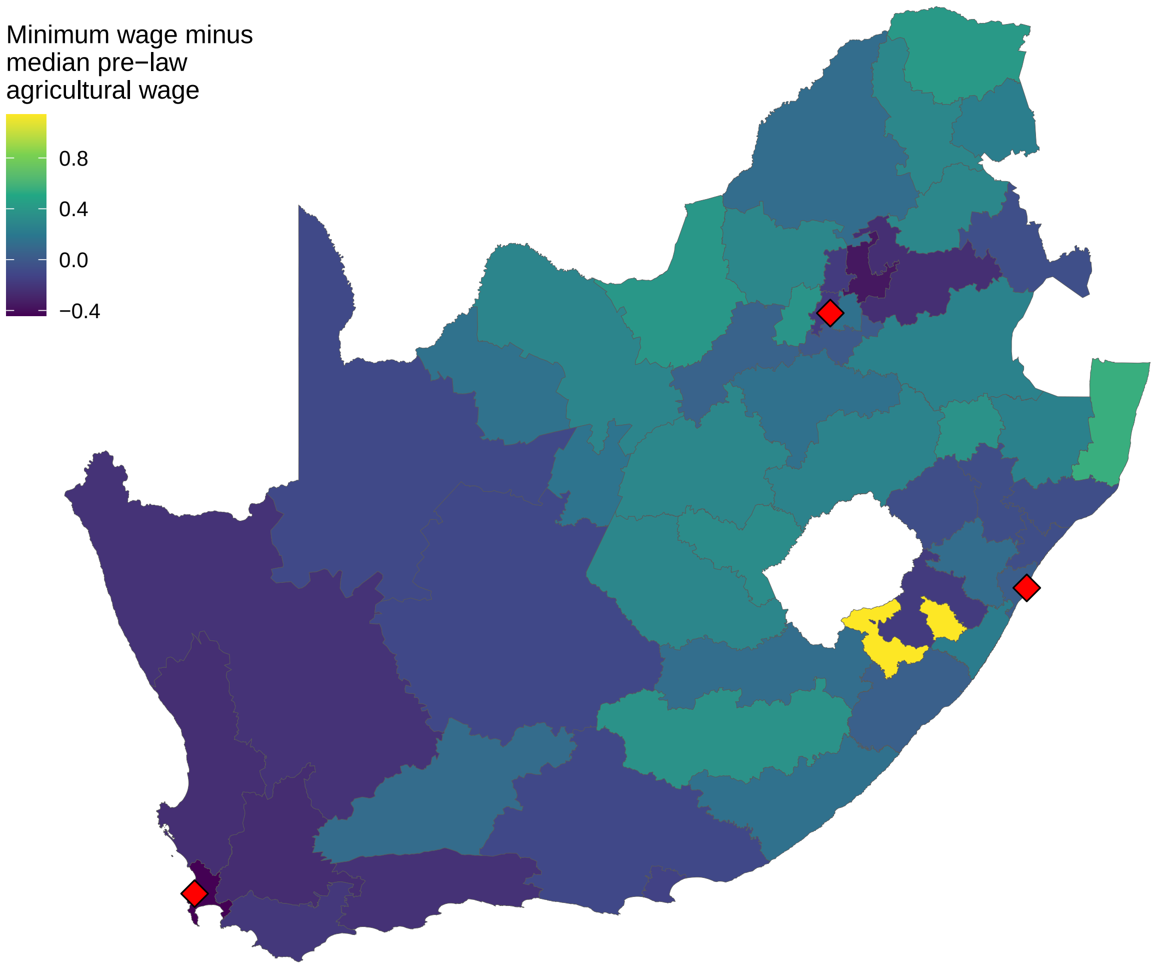
We focus mostly on the agricultural sector in this paper. We first examine the effects of the minimum wage law using the following specification:

$$y_{idt} = \alpha_d + \gamma_t + \beta Post_t \times WG_d + X_{idt} + \varepsilon_{idt}, \tag{10}$$

where y_{idt} is the outcome of interest for person i in district d in wave t, α_d is district fixed effects, γ_t is survey wave fixed effects, $Post_t$ is a dummy that takes the value of one after implementation of the minimum wage law, X_{idt} is a vector of individual-level covariates: age, age squared, gender, (years of) education, education squared, and race. The coefficient of interest is β, which is a type of differences-in-differences estimator, similar in spirit to Duflo (2001). Due to the fixed effects, both $Post_t$ and WG_d drop out of the equation, leaving just the interaction term. Since the law took effect simultaneously across the country, there are no concerns regarding possible bias in two-way fixed effects models (e.g. (e.g. Callaway and Sant'Anna, 2021; De Chaisemartin and d'Haultfoeuille, 2020; Goodman-Bacon, 2021). Nonetheless, the key identification assumption of parallel trends is still required. We present evidence in support of this assumption in the results section.

We are interested in several key outcomes: agricultural employment, hours worked in

Figure 2: Pre-law wage gaps across district councils



Notes: The three points are the three largest cities in South Africa: Johannesburg to the north – very close to the administrative capital, Pretoria, which is not shown on the map – Cape Town to the southwest, and Durban to the southeast. The wage gap is defined as the difference between the mandated minimum wage (log ZAR) and the median pre-law wage (log ZAR) in each district council, such that higher values indicate areas with lower wages.

agriculture, hourly wage in agriculture, and total monthly income in agriculture. We analyse these outcomes with respect to different subsamples of the data. For example, in some specifications, we include only individuals working in the agricultural sector, in others we include everyone in the labour force, and in yet others we include everyone.

Our primary goal in this paper is to examine how the minimum wage impacts labour market flexibility in a developing country. One peculiarity of developing country labour markets is how much they are affected by the weather. While wages are rigid (Kaur, 2019), they are also known to be volatile and move in response to weather shocks (Jayachandran, 2006). A key question is how labour markets will adjust in response to shocks when there is a wage floor in the form of a minimum wage. To answer this question, we define a rainfall variable – $rainShock$ – that is meant to capture agricultural productivity. We define this variable identically to Jayachandran (2006): it takes on the value of one if yearly rainfall is above the 80th percentile of that district's rainfall distribution, negative one if it is below the 20th percentile, and zero otherwise. We then estimate regressions of the form:

$$\begin{aligned} y_{idt} = \alpha_d + \gamma_t + \beta_1 Post_t \times WG_d + \beta_2 Post_t \times WG_d \times I(rainShock == -1) + \\ \beta_3 Post_t \times WG_d \times I(rainShock == 1) + X_{idt} + \varepsilon_{idt}, \end{aligned} \tag{11}$$

Essentially, we compare the effects of the minimum wage based on the wage gap variable and whether it was a good agricultural year or not.

The model predicts that the minimum wage will have hetereogeneous impacts depending on the agricultural productivity shocks. In particular, the change in employment should be correlated with how binding the new minimum wage is. This suggests that a negative productivity shock will have a more negative effect on equilibrium labour allocation following the imposition of the minimum wage, relative to no shock, assuming that the new minimum wage is binding in at least the former. On the other hand, a positive productivity shock will have a more positive effect on equilibrium labour allocation following the imposition of the minimum wage, relative to no shock, if the minimum wage is binding in the latter.

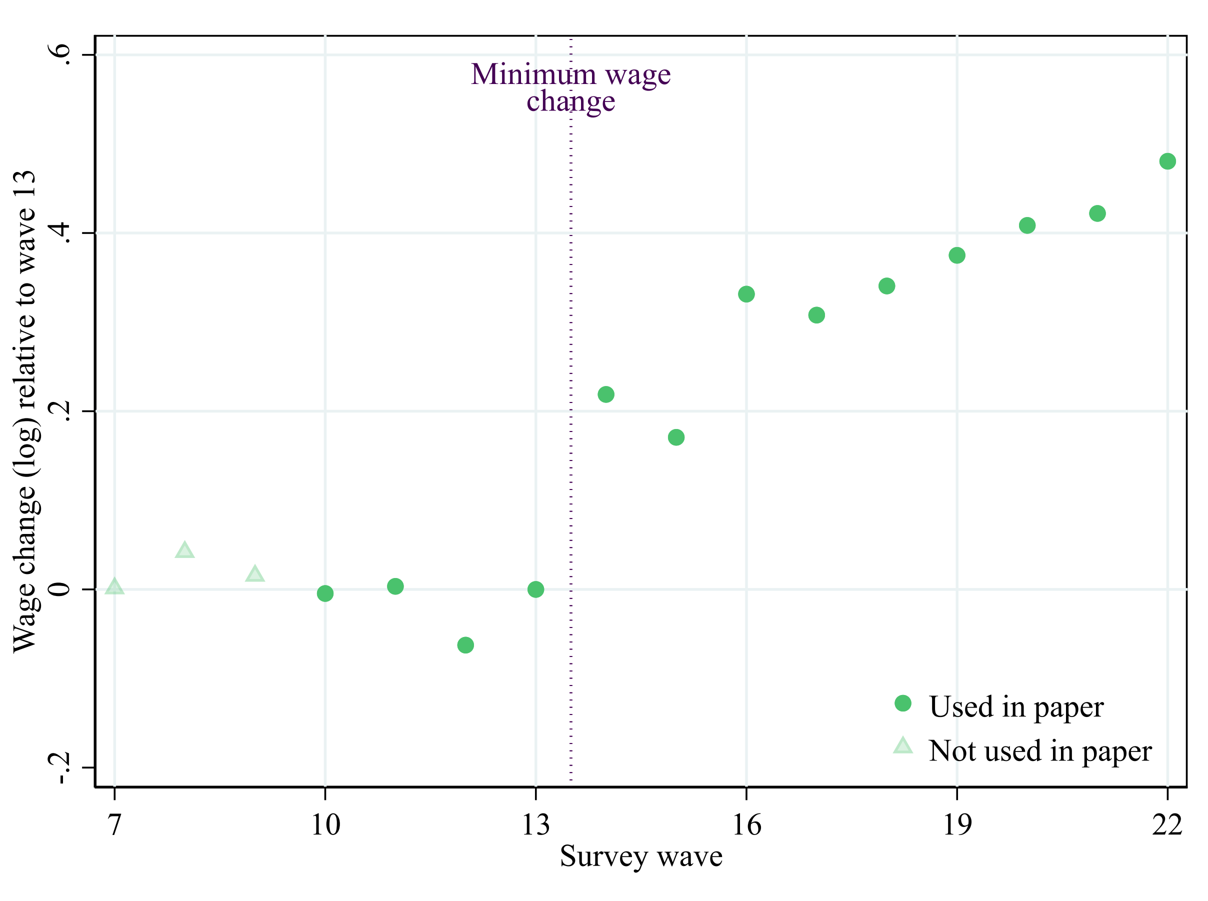
4.3 Testing for parallel trends

Since the estimator is a differences-in-differences estimator, the assumption of parallel trends remains important for causal identification. In our case, we have data from before and after the minimum wage change. While this does not allow us to explicitly test the parallel trends assumption – an assumption that is inherently untestable – it does allow us to present evidence from prior to the wage change that suggests the assumption is plausible.

Figure 3 presents average agricultural wages across the waves of the survey. The dashed line shows the point in time at which the minimum wage changes. There are seven survey waves from before the change and nine waves from after.[6] There are two important patterns to note. First, average wages were constant prior to the minimum wage change; there was no noticeable upward trend of average wages. Second, there is a noticeable, immediate increase in average agricultural wages immediately upon implementation of the new minimum wage.

[6]Recall that we do not use the first three waves in our main results due to a chance in the sampling structure. In the appendix we present robustness checks for our main results using these waves, however.

Figure 3: Average wages across waves



Notes: The three triangles indicate the survey ways prior to the change in the sample design. We do not include these waves in our main results, but do include them in the pre-trends tests.

We believe Figure 3 provides prima facie evidence that the parallel trends assumption is valid. However, it is not an exact graphical depiction of our identification strategy since we are actually using variation in the district's distance from the new minimum wage prior to its implementation. We present two sets of empirical results to back the parallel trends assumptions. First, Table 1 presents the common test for pre-trends. We create a new "post" variable that takes the value of one in the three waves just prior to implementation of the new law and a zero for the waves prior to that. If trends prior to implementation are driving our results, the coefficients in Table 1 should be similar to those in our main results. For the most part, this is not the case. The coefficient for hours for women is the

Table 1: Testing for pre-trends

	(1) LF only Employ.	(2) All adults Employ.	(3) LF only Hours	(4) All adults Hours	(5) Ag only Wage	(6) Ag only Income
Panel A: All						
Post (proxy) times	−0.033	−0.023	4.930	−2.896	−0.077	−0.095
wage gap	(0.028)	(0.018)	(10.024)	(1.859)	(0.077)	(0.060)
Observations	202,619	333,831	23,439	333,831	14,961	14,802
Panel B: Women						
Post (proxy) times	−0.049	−0.030	11.496	−3.284	−0.082	−0.033
wage gap	(0.041)	(0.023)	(12.015)	(2.385)	(0.123)	(0.093)
Observations	96,368	179,367	8,790	179,367	4,524	4,502
Panel C: Men						
Post (proxy) times	−0.018	−0.015	−1.761	−2.551	−0.062	−0.134*
wage gap	(0.018)	(0.014)	(10.266)	(1.851)	(0.070)	(0.063)
Observations	106,251	154,464	14,649	154,464	10,435	10,299

Notes: Standard errors are in parentheses and are clustered at the magisterial district and the survey wave level. The "Post (proxy)" variable takes the value of one in the three waves just prior to implementation of the new law and a zero for the waves prior to that. Column (1) includes only individual in the labour force. Columns (2) and (4) include all adults. Column (3) includes only individuals in the agricultural sector. Columns (5) and (6) include only individuals in the agricultural wage sector.
* p<0.1 ** p<0.05 *** p<0.01

only coefficient that might suggest caution, while all of the coefficients for men and for women are insignificant or in the wrong direction.

The second set of empirical results looks at heterogeneity in the effects of the minimum wage law over time. Since we have nine waves after the wage change, we can look at the evolution of the effect over these different waves. Specifically, we look at the effects of the new law in year one, year two, year three, and year four following the change. We present these results in Table 2. The key pattern is that effects are relatively consistent across all four years. This is especially true for wages, for which the coefficients vary from just 0.306 to 0.340. In other words, if a failure of the parallel trends assumption is responsible for our results, it must be the case that this failure was not apparent before the new wage took effect (Table 1) and that these differential trends did not persist at all following the initial change.

Table 2: Effects on agriculture over time

	(1) First year	(2) Second year	(3) Third year	(4) Fourth year
Panel A: Employment				
Post times wage gap	−0.009	0.007	0.011	0.000
	(0.008)	(0.012)	(0.023)	(0.018)
Observations	182,366	184,888	186,677	187,027
Panel B: Hours				
Post times wage gap	10.166	15.568	18.862	9.949
	(8.396)	(9.433)	(12.716)	(8.037)
Observations	19,505	20,912	21,046	21,064
Panel C: Wage				
Post times wage gap	0.320***	0.306**	0.318***	0.340***
	(0.055)	(0.093)	(0.075)	(0.048)
Observations	13,816	14,049	13,917	14,002

Notes: Standard errors are in parentheses and are clustered at the magisterial district and the survey wave level. Each year is composed of two separate survey waves.
* p<0.1 ** p<0.05 *** p<0.01

5 Results

5.1 Minimum wage effects

We begin by analysing the effects of the introduction of the minimum wage on different agricultural employment variables. We present this first set of results in Table 3. The outcome in column (1) is a simple dummy for whether an individual is employed in the agricultural sector or not. We restrict the sample to everyone in the labour force. Column (2), on the other hand, expands the sample to include all adults (assuming anyone not in the labour force is not employed in the agricultural sector). In both cases, we see no changes in the overall probability of agricultural employment in response to the imposition of the new minimum wage.

Of course, just because there is no change on the extensive margin does not mean there are no changes in overall employment on the intensive margin. Columns (3) and (4) look at total hours in agriculture. Column (3) restricts the sample to only those engaged in agricultural employment. Interestingly, overall monthly agricultural hours go up in response to the minimum wage, not down. When we expand the sample to all adults, we do not see any increases, but we also do not see any decreases. In fact, we can rule out an average decrease of anything more than around 3.4 hours per month. These results are quite different from those in Bhorat et al. (2014). There are two possible explanations. First, they use all of the pre-minimum wage waves while we restrict the pre-change waves following Dinkelman and Ranchhod (2012). However, Table A1 in the appendix shows that using these waves does not recover their overall estimates. While the coefficients are now more negative, they are still far from significant and much smaller in magnitude than those in Bhorat et al. (2014). A second possible explanation for the differing results is changes we made to the matching of districts across waves as well as to the matching of minimum wage levels to district boundaries to improve the precision of assignment of minimum wage levels to workers.

Lastly, columns (5) and (6) look at average (log) hourly wages and total (log) monthly income, respectively. The wage is only defined for those engaged in wage employment, so the sample is restricted to this subsample in both columns.[7] Perhaps unsurprisingly, we see large increases in the average hourly wage in response to the new minimum wage. The coefficient is not directly interpretable as the "effect" of the minimum wage since the independent variable is not a dichotomous variable but rather a continuous variable based on how far the district's average agricultural wage was from the new minimum wage. To put the coefficient in context, the interquartile range for the sample in column (5) is approximately 0.42. Combining this with the coefficient shows that moving from the 25th percentile to the 75th percentile leads to a wage increase of slightly less than 16 percent. Since the wage increased and hours went up slightly, we also see an increase in agricultural income for those who engage in agricultural wage employment.

Previous research has shown that women are sometimes impacted more by minimum

[7]We expand these regressions by imputing agricultural income for the self-employed below.

Table 3: Effects of the minimum wage on agricultural employment

	(1) LF only Employ.	(2) All adults Employ.	(3) Ag only Hours	(4) All adults Hours	(5) Ag only Wage	(6) Ag only Income
Post times wage gap	0.002	−0.001	13.354*	0.420	0.341***	0.351***
	(0.013)	(0.009)	(6.185)	(1.771)	(0.040)	(0.034)
Female	−0.034***	−0.035***	−29.120***	−8.131***	−0.129***	−0.188***
	(0.008)	(0.007)	(3.198)	(1.555)	(0.016)	(0.018)
Age (10s)	−0.045**	0.047***	26.814***	10.551***	0.360***	0.352***
	(0.016)	(0.009)	(4.410)	(1.920)	(0.033)	(0.037)
Age (10s) squared	0.006**	−0.006***	−3.835***	−1.403***	−0.037***	−0.037***
	(0.002)	(0.001)	(0.544)	(0.266)	(0.004)	(0.005)
Education (years)	−0.024***	−0.010***	−0.642	−2.102***	−0.008	0.001
	(0.002)	(0.001)	(0.397)	(0.244)	(0.006)	(0.005)
Education squared	0.001***	0.000***	−0.068**	0.045***	0.003***	0.002***
	(0.000)	(0.000)	(0.029)	(0.014)	(0.001)	(0.000)
Observations	393,622	690,371	45,251	690,371	30,319	30,117

Notes: Standard errors are in parentheses and are clustered at the magisterial district and the survey wave level. Column (1) includes only individual in the labour force. Columns (2) and (4) include all adults. Column (3) includes only individuals in the agricultural sector. Columns (5) and (6) include only individuals in the agricultural wage sector.
* p<0.1 ** p<0.05 *** p<0.01

Table 4: Effects on agriculture by gender

	(1) LF only Employ.	(2) All adults Employ.	(3) Ag only Hours	(4) All adults Hours	(5) Ag only Wage	(6) Ag only Income
Panel A: Women						
Post times wage gap	0.000	−0.002	6.611	−0.366	0.297***	0.267***
	(0.018)	(0.009)	(8.265)	(1.556)	(0.095)	(0.061)
Observations	185,996	373,622	15,902	373,622	9,050	9,059
Panel B: Men						
Post times wage gap	0.002	−0.001	16.244**	1.040	0.346***	0.383***
	(0.010)	(0.011)	(7.118)	(2.513)	(0.045)	(0.039)
Observations	207,626	316,749	29,349	316,749	21,269	21,058

Notes: Standard errors are in parentheses and are clustered at the magisterial district and the survey wave level. Column (1) includes only individual in the labour force. Columns (2) and (4) include all adults. Column (3) includes only individuals in the agricultural sector. Columns (5) and (6) include only individuals in the agricultural wage sector.
* p<0.1 ** p<0.05 *** p<0.01

wage increases than men (Arango-Arango, 2004; Feliciano, 1998). We also note large differences in average wages across genders, leading to a possible mechanism for differences in the effect of the wage floor. As such, we next split the sample by gender and look at whether effects vary. We present these results in Table 4. The positive effects are slightly larger in magnitude for men than for women. However, in none of the cases is this difference significant.[8] We nonetheless continue to present results separately for men and women, as further results reveal some important heterogeneity.

Overall, these results would lead one to conclude that the minimum wage increase had few negative effects, at least when looking at average treatment effects. We see no decreases in agricultural employment – on the extensive or intensive margin – and large increases in hourly wages. Unsurprisingly, this also leads to large increases in monthly agricultural income. In addition, both men and women appear to have benefited from the minimum wage increase, with neither group seeing decreases in employment and both seeing increases in wages and income. On the whole, there seem to be few negative effects for workers.

5.2 Agricultural shocks and binding minimum wages

When looking at the average effects of the minimum law change, there seem to be no negative effects. However, labour market policies can also affect how the labour market responds to shocks. In developing countries, for example, agricultural productivity shocks – usually proxied by deviations of rainfall from historical averages – can have important effects on employment and wages (Jayachandran, 2006). We might expect minimum wages to be more binding during bad rainfall years, when there is downward pressure on wages. In these cases, it is reasonable to expect larger disemployment effects of the minimum wage (Neumark, 2019). In this section, we show how a new wage floor interacts with these agricultural productivity shocks and how this interaction can lead to perverse

[8]We explicitly test for differences with a pooled regression.

outcomes; outcomes that were not apparent in the average effects.[9]

Table 5 presents the first set of results. We interact the differences-in-differences estimator ($Post_t \times WG_d$) with an indicator for whether rainfall in the year was bad, normal, or good. Normal is the omitted category, so the interpretation of $Post_t \times WG_d$ in Table 5 is the change due to the minimum wage increase during normal rainfall years, when rainfall is between the 20th and 80th percentile in a given district's historical rainfall distribution. Panel A presents results for everyone. During normal years, there is an increase in hours worked for those in agricultural wage employment, but no significant increase when we expand the sample to include everyone in the labour force or all adults (columns (4) and (5), respectively). We also see an increase in wages, consistent with the main results.[10]

We start to see important differences when we look at effects during negative agricultural shocks. There are large negative effects on employment on the intensive margin. Importantly, these effects persist when we expand the sample to include all adults. In other words, there is a significant decrease in hours devoted to agricultural wage employment during poor rainfall years. Moreover, the linear combination of the first two rows is significantly negative for all three hours samples. During good years, we see opposite effects, with a large increase in hours spent in agricultural wage employment. The effect is quite quite substantial relative to mean hours worked. In the sample in column (5), the overall mean during negative shocks is 7.11 hours (the median is zero). Going from the 25th to the 75th percentile of the wage exposure variable leads to a decrease in hours worked of around 35.5 percent relative to the mean. For positive shocks, on the other hand, the increase is around 41.9 percent relative to the positive shock mean of 9.42 hours.

Interestingly, the pattern of effects differ in more than just sign. Most of the effect during positive rainfall years is on the extensive margin, with people entering the agricultural

[9]Table A3 in the appendix shows that wages vary with agricultural shocks in the expected directions prior to the minimum wage increase. However, given the shorter time period, differences across shocks are not significant at traditional levels.

[10]Table A2 in the appendix shows the effects of shocks prior to the minimum wage change; we do not see the same patterns and heterogeneity that we see following the law change.

Table 5: Effects of rainfall shocks

	(1) LF only Employ.	(2) All Employ.	(3) Ag only Hours	(4) LF only Hours	(5) All Hours	(6) Ag only Wage
Panel A: All						
Post times wage gap	0.006	0.000	15.858*	2.251	0.881	0.361***
	(0.017)	(0.013)	(7.510)	(3.213)	(2.299)	(0.065)
Post times wage gap	−0.038	−0.018	−42.381**	−12.463**	−6.901*	−0.118
times negative shock	(0.032)	(0.025)	(18.395)	(4.397)	(3.452)	(0.305)
Post times wage gap	0.077*	0.053**	3.372	14.481**	8.517***	−0.069
times positive shock	(0.039)	(0.022)	(12.586)	(4.896)	(2.743)	(0.097)
Linear combinations (p)						
Negative	0.173	0.298	0.045	0.009	0.027	0.398
Positive	0.021	0.016	0.166	0.001	0.002	0.006
Observations	393,622	690,371	45,251	393,622	690,371	30,319
Panel B: Women						
Post times wage gap	0.004	−0.001	17.849	1.345	0.183	0.232**
	(0.025)	(0.014)	(12.764)	(4.155)	(2.330)	(0.100)
Post times wage gap	−0.028	−0.008	−68.167***	−11.099*	−5.010	0.182
times negative shock	(0.046)	(0.029)	(17.322)	(6.140)	(3.656)	(0.267)
Post times wage gap	0.094*	0.055**	−23.100	11.750*	6.503**	0.159
times positive shock	(0.046)	(0.023)	(15.654)	(5.970)	(2.893)	(0.132)
Linear combinations (p)						
Negative	0.505	0.690	0.000	0.109	0.174	0.103
Positive	0.020	0.018	0.722	0.004	0.003	0.013
Observations	185,996	373,622	15,902	185,996	373,622	9,050
Panel C: Men						
Post times wage gap	0.004	0.001	13.914**	2.385	1.307	0.395***
	(0.013)	(0.013)	(5.831)	(2.961)	(2.672)	(0.071)
Post times wage gap	−0.045**	−0.030	−25.604	−13.396***	−9.161**	−0.296
times negative shock	(0.020)	(0.022)	(21.216)	(3.944)	(3.902)	(0.317)
Post times wage gap	0.057*	0.050*	16.118	16.549***	11.491***	−0.133
times positive shock	(0.031)	(0.024)	(14.319)	(5.232)	(3.358)	(0.098)
Linear combinations (p)						
Negative	0.013	0.049	0.556	0.005	0.010	0.739
Positive	0.025	0.063	0.061	0.008	0.014	0.003
Observations	207,626	316,749	29,349	207,626	316,749	21,269

Notes: Standard errors are in parentheses and are clustered at the magisterial district and the survey wave level. Columns (1) and (4) include only individuals in the labour force. Columns (2) and (5) include all adults. Column (3) includes only adults in the agricultural sector. Column (6) includes only adults in the agricultural wage sector. A negative shock is defined as rainfall below the 20th percentile of the historical distribution for a given district, while a positive shock is defined as rainfall above the 80th percentile.

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

wage labour force. The opposite seems to be true during negative shocks; much of the decrease in hours is driven by people working in the agricultural wage sector. There are no differences in the effects on wages, indicating that employment is a new way in which the labour market adjusts to shocks, since wages are now bounded below by the new minimum wage.

Panel B and Panel C split the sample into women and men, respectively. Important heterogeneity is found again: First, women working in agricultural wage employment see large negative effects on monthly hours during bad years. The coefficient implies a decrease in hours equivalent to approximately 35 percent of the median. However, as we expand the sample, this effect gets smaller and smaller until it is no longer significant when we include all adult women. Apparently, the disemployment effect is quite large among women who are working, even though we see no large changes on the extensive margin in columns one and two. The coefficient for men is smaller – and insignificant – when we restrict the sample to only those working in agriculture but is larger – and significant – when we expand the sample to men in the labour force or all men. On the other hand, we also see an increase in hours during good years relative to normal years (the interaction term) as well as increases in the effects of a positive shock after the minimum wage relative to before (the linear combination). The effects relative to the mean are quite similar in magnitude to those for the overall sample.

This overall pattern of results is consistent with the theoretical model. Specifically, we see no changes in the wage with respect to normal years – though the estimate is quite imprecise – but also see more negative effects on employment in bad years relative to normal years as well as more negative effects in normal years relative to good years. When the wage is unable to adjust downward, the economy instead adjusts on the employment margin.

One weakness of the wage results in Table 5 is that they consider only agricultural wage employment. If people are moving in and out of agricultural self-employment, for exam-

Table 6: Effects on agricultural income, all adults

	(1) 25th pctile	(2) 50th pctile	(3) 75th pctile	(4) Estimated
Panel A: All				
Post times wage gap	−0.004	−0.007	−0.009	−0.001
	(0.066)	(0.069)	(0.071)	(0.064)
Post times wage gap	−0.103	−0.099	−0.096	−0.107
times negative shock	(0.118)	(0.126)	(0.132)	(0.117)
Post times wage gap	0.401***	0.422***	0.440***	0.403***
times positive shock	(0.099)	(0.104)	(0.108)	(0.097)
Linear combinations (p)				
Negative	0.242	0.277	0.306	0.256
Positive	0.002	0.002	0.002	0.001
Observations	690,371	690,371	690,371	690,371
Panel B: Women				
Post times wage gap	−0.025	−0.028	−0.032	−0.021
	(0.071)	(0.074)	(0.076)	(0.068)
Post times wage gap	−0.051	−0.044	−0.038	−0.055
times negative shock	(0.139)	(0.148)	(0.156)	(0.138)
Post times wage gap	0.381***	0.407***	0.430***	0.375***
times positive shock	(0.102)	(0.108)	(0.113)	(0.097)
Linear combinations (p)				
Negative	0.536	0.578	0.611	0.553
Positive	0.003	0.003	0.003	0.002
Observations	373,622	373,622	373,622	373,622
Panel C: Men				
Post times wage gap	0.010	0.009	0.008	0.012
	(0.074)	(0.076)	(0.077)	(0.073)
Post times wage gap	−0.163	−0.163	−0.164	−0.168
times negative shock	(0.105)	(0.109)	(0.114)	(0.102)
Post times wage gap	0.437***	0.452***	0.464***	0.449***
times positive shock	(0.112)	(0.117)	(0.121)	(0.113)
Linear combinations (p)				
Negative	0.055	0.060	0.065	0.050
Positive	0.010	0.011	0.011	0.007
Observations	316,749	316,749	316,749	316,749

Notes: Standard errors are in parentheses and are clustered at the magisterial district and the survey wave level. Columns (1) and (4) include only individuals in the labour force. Columns (2) and (5) include all adults. Column (3) includes only adults in the agricultural sector. Column (6) includes only adults in the agricultural wage sector. A negative shock is defined as rainfall below the 20th percentile of the historical distribution for a given district, while a positive shock is defined as rainfall above the 80th percentile. We impute agricultural self-employment income in columns (1)-(3) by assuming an hourly income equal to the specified point in the wage distribution. In column (4), we estimate hourly income by imputing it using a set of demographic characteristics. * p<0.1 ** p<0.05 *** p<0.01

ple, this adjustment mechanism will be missed. This issue arises because self-employment income was not captured in the survey. To look at total agricultural employment income – including self employment – we take two broad approaches. First, we simply impute self-employment hourly wages using different percentiles of the agricultural wage distribution. We choose three separate percentiles – the 25th, the 50th, and the 75th – and then multiply total monthly hours by these different hourly wages to arrive at total monthly income for those who are self employed. However, this assumes everyone in agricultural self-employment is making the same hourly wages, which is unlikely. As such, for our second approach we instead impute hourly wages individually, using a set of observable characteristics. We purposefully keep this simple, regressing hourly wages on gender, age, age squared, years of education, years of education squared, three race dummies, wave fixed effects and district fixed effects. We then predict hourly income for those who are engaged in agricultural self-employment.[11]

Table 6 presents results of the effect of the minimum wage on total agricultural income using these four separate imputations, restricting the sample to all adults in the labour force. The results are markedly more imprecise than previous results using agricultural income (e.g. column (6) of Table 4). However, the overall pattern of results is identical to those in Table 5: we see more negative effects during poor rainfall years and more positive effects during positive rainfall years, particularly for men. Reassuringly, the imputation procedure does not seem to have larger impacts on the estimated coefficient. Overall, it seems that the minimum wage has led to more variable agricultural income, though we only have the power to definitively say this for men.

Finally, it could also be that people are sorting into different sectors in response to agricultural productivity shocks. If people lose employment in agriculture but turn around and gain employment in non-agricultural sectors, the overall effects of the minimum wage

[11]The wage regression has an R-squared of 0.361 and an adjusted R-squared of 0.360. Those who are unemployed or out of the labour force receive monthly income of zero. We add a random error term – with a mean of zero and a standard deviation equal to the standard deviation of the hourly wage – to each individual's predicted wage.

Table 7: Effects on total employment and hours

	(1) LF only Employ.	(2) All adults Employ.	(3) LF only Hours	(4) All adults Hours
Panel A: All				
Post times wage gap	0.003	−0.021	1.632	−3.332
	(0.020)	(0.020)	(4.471)	(3.442)
Post times wage gap	−0.015	−0.017	−4.326	−4.863
times negative shock	(0.031)	(0.031)	(10.427)	(7.594)
Post times wage gap	0.001	0.039	−0.325	6.505
times positive shock	(0.030)	(0.024)	(9.858)	(5.093)
Linear combinations (p)				
Negative	0.711	0.109	0.799	0.242
Positive	0.864	0.513	0.885	0.593
Observations	393,622	690,371	393,716	690,371
Panel B: Women				
Post times wage gap	0.010	−0.020	1.217	−3.874
	(0.019)	(0.018)	(4.785)	(2.927)
Post times wage gap	0.011	0.018	4.092	3.256
times negative shock	(0.034)	(0.038)	(11.760)	(8.436)
Post times wage gap	−0.036	0.038	−8.842	5.871
times positive shock	(0.036)	(0.023)	(14.626)	(6.233)
Linear combinations (p)				
Negative	0.560	0.969	0.648	0.938
Positive	0.346	0.567	0.553	0.757
Observations	185,996	373,622	186,042	373,622
Panel C: Men				
Post times wage gap	−0.004	−0.021	1.875	−2.449
	(0.027)	(0.028)	(5.432)	(5.289)
Post times wage gap	−0.038	−0.060	−11.471	−14.923*
times negative shock	(0.044)	(0.038)	(10.311)	(8.011)
Post times wage gap	0.040	0.053	9.192	10.332*
times positive shock	(0.037)	(0.031)	(6.990)	(4.865)
Linear combinations (p)				
Negative	0.363	0.018	0.343	0.019
Positive	0.265	0.267	0.138	0.224
Observations	207,626	316,749	207,674	316,749

Notes: Standard errors are in parentheses and are clustered at the magisterial district and the survey wave level. Columns (1) and (3) include only individuals in the labour force. Columns (2) and (4) include all adults. A negative shock is defined as rainfall below the 20th percentile of the historical distribution for a given district, while a positive shock is defined as rainfall above the 80th percentile.
* $p<0.1$ ** $p<0.05$ *** $p<0.01$

could be muted. We are not as comfortable imputing non-agricultural self-employment income – since "non-agriculture" is such a heterogeneous group – so we instead focus just on total hours worked and overall employment. We present these results in Table 7. Columns one and two include overall employment while columns three and four include total (monthly) hours of employment, with the sample restricted to those in the labour force in the first column of each pair.

Overall, we see a negative effect on overall employment during poor rainfall years, but this effect is not significant and is small in magnitude. There is no decrease for women when we include all forms of employment. Recall, however, that we did not see large negative effects for women when we included all adults, so the overall patterns are somewhat in agreement.

This is not the case for men, however. We continue to see large negative effects on employment on both the extensive and the intensive margin when we include all adults. The coefficient of -14.9 hours in column (4) is actually a rather larger effect.[12] When including all adult men, median monthly hours is zero and the mean is 102.4. Using the interquartile range of 0.42 cited earlier and taking the linear combination at face value, that is a decrease in hours worked of more than seven percent during negative rainfall shocks when moving from the 25th to the 75th percentile of the wage gap distribution. Overall, these results suggest that the effects in agriculture do not disappear when we consider all types of employment. Instead, it appears that men, specifically, are not able to make up for the loss of agricultural employment by finding work in other sectors. In fact, the point estimates themselves show no evidence of men offsetting *any* of the agricultural employment losses.

In Table A4 of the appendix, we also present these results without two district municipalities that have the highest wage gaps: Alfred Nzo DM and Bohlabela DM.[13] The pattern

[12]The overall effect is the linear combination with the coefficient during "normal" years.
[13]These are the two yellow DMs in the eastern central part of the map.

of significant changes across all panels is identical.

As a final sanity check of the results and to make sure expectations align with the story, we present one last set of results in Table 8. Specifically, we look at whether people employed are more/less likely to be employed formally. The dependent variable in all four columns is whether the employee has unemployment insurance deducted from their pay. In each pair of columns, the first column includes people employed in the agricultural sector and the second column includes only people employed in the non-agricultural sector. The general idea is that minimum wages are likely to be more binding in the formal sector than the informal sector. We do not see any changes for women, but we do see changes for men. Specifically, during negative productivity shocks, men in the agricultural sector are less likely to be employed formally. The drop is very large, with the coefficient indicating that an increase in the wage gap from the 25th to the 75th percentile leads to a drop of around nine percentage points in the probability of being employed formally. We do not see this in the non-agricultural sector, however. It seems that negative weather shocks lead to the casualisation of the agricultural labour force in the post-law period. This is a notable finding since, in general, the proportion of agricultural wage workers with written contracts went up in the post law period.

6 Conclusion

In this paper, we analyse the effects of a new minimum wage law in the agricultural sector in South Africa. We find that the law led to large wage increases and even an employment increase for some subsets of the population engaged in agriculture. Total agricultural income likewise increased in response to the new law. Overall, the initial effects of the law paint an optimistic picture of the welfare effects of the minimum wage in this context, with small increases in employment and large increases in wages and income.

However, we document important heterogeneity in the effects of the minimum wage

Table 8: Effects on formality

	Women		Men	
	(1)	(2)	(3)	(4)
	Ag only	Non-ag only	Ag only	Non-ag only
Post times wage gap	0.155**	0.040	−0.050	0.083*
	(0.063)	(0.043)	(0.066)	(0.043)
Post times wage gap	−0.002	0.037	−0.222**	0.007
times negative shock	(0.092)	(0.039)	(0.084)	(0.106)
Post times wage gap	−0.036	0.039	0.042	−0.073
times negative shock	(0.053)	(0.068)	(0.066)	(0.049)
Linear combinations (p)				
Negative	0.075	0.038	0.007	0.309
Positive	0.075	0.061	0.927	0.723
Observations	16,885	101,390	29,915	119,395

Notes: Standard errors are in parentheses and are clustered at the magisterial district and the survey wave level. The outcome in columns (1) and (4) is whether the employee has a contract (either written or verbal). In the other columns, the outcome is a dummy for formality defined by the survey team. Columns (3) and (6) include only people employed outside of agriculture. The other columns include only people employed in agriculture.
* p<0.1 ** p<0.05 *** p<0.01

based on the state of agricultural productivity. While we see increases in wages and employment during normal years, we see decreases in total employment during poor rainfall years, with positive agricultural productivity shocks seeing the opposite effects. In effect, while the minimum wage increased the mean, it also increased the variance. These effects are especially clear for men, with overall decreases in employment seen even when we consider the entire population.

Importantly, individuals do not seem to be able to reallocate to the non-agricultural sector during these negative shocks. We see overall employment decrease, specifically for men. In fact, it does not appear that men are able to offset any of the negative effects in the agricultural sector.

Our results suggest caution in interpreting the effects of minimum wage interventions on the first moment alone, especially when local contexts mean minimum wages may be more or less binding across years. This may be particularly true in developing countries, where large-scale employment shocks are rather common, especially in places where agricultural predominates. We encourage future research to continue focusing on the effects of this type of policy on higher moments of the employment and wage distribution.

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Appendix

Table A1: Effects of the minimum wage on agricultural employment, all waves

	(1) Employ.	(2) Employ.	(3) Hours	(4) Hours	(5) Wage	(6) Income
Post times wage gap	−0.021	−0.017	19.912***	−1.042	0.292***	0.315***
	(0.022)	(0.016)	(4.764)	(2.324)	(0.056)	(0.052)
Female	−0.032***	−0.034***	−29.955***	−8.218***	−0.139***	−0.196***
	(0.008)	(0.007)	(2.899)	(1.560)	(0.020)	(0.020)
Age (10s)	−0.061***	0.045***	31.994***	10.458***	0.421***	0.380***
	(0.020)	(0.008)	(5.165)	(1.847)	(0.044)	(0.038)
Age (10s) squared	0.008**	−0.006***	−4.414***	−1.381***	−0.044***	−0.040***
	(0.003)	(0.001)	(0.621)	(0.254)	(0.006)	(0.005)
Education (years)	−0.025***	−0.011***	−0.611	−2.376***	−0.006	0.004
	(0.002)	(0.001)	(0.428)	(0.264)	(0.005)	(0.004)
Education squared	0.001***	0.000***	−0.127**	0.056***	0.004***	0.002***
	(0.000)	(0.000)	(0.057)	(0.015)	(0.001)	(0.000)
Observations	470,851	814,527	55,165	814,527	36,033	35,747

Notes: Standard errors are in parentheses and are clustered at the magisterial district and the survey wave level. Column (1) includes only individual in the labour force. Columns (2) and (4) include all adults. Column (3) includes only individuals in the agricultural sector. Columns (5) and (6) include only individuals in the agricultural wage sector.
* p<0.1 ** p<0.05 *** p<0.01

Table A2: Effects of rainfall shocks, pre-minimum wage

	(1) Employ.	(2) Employ.	(3) Hours	(4) Hours	(5) Hours	(6) Wage
Wage gap times	−0.033	−0.023	24.124	−3.175	−2.539	−0.065
negative shock	(0.029)	(0.020)	(14.860)	(3.017)	(2.266)	(0.138)
Wage gap times	−0.025	−0.014	−3.329	−5.976	−3.017	0.174
positive shock	(0.041)	(0.022)	(17.067)	(3.790)	(2.276)	(0.109)
Observations	202,619	333,831	23,439	202,619	333,831	14,961

Notes: Standard errors are in parentheses and are clustered at the magisterial district and the survey wave level. Columns (1) and (4) include only individuals in the labour force. Columns (2) and (5) include all adults. Column (3) includes only individuals in the agricultural sector. Column (6) include only individuals in the agricultural wage sector.
* p<0.1 ** p<0.05 *** p<0.01

Table A3: Effects of rainfall shocks on wages, pre-minimum wage

	(1) Wage	(2) Income
Negative shock times wage gap	−0.065	−0.043
	(0.138)	(0.093)
Positive shock times wage gap	0.174	0.148*
	(0.109)	(0.061)
Negative = positive	0.183	0.180
Observations	14,961	14,802

Notes: Standard errors are in parentheses and are clustered at the magisterial district and the survey wave level. The sample is restricted to waves before the implementation of the minimum wage. The dependent variable in column (1) is hourly (agricultural) wage. The dependent variable in column (2) is total monthly agricultural income.
* p<0.1 ** p<0.05 *** p<0.01

Table A4: Effects on total employment and hours, no outliers

	(1) LF only Employ.	(2) All adults Employ.	(3) LF only Hours	(4) All adults Hours
Panel A: All				
Post times wage gap	0.003	−0.036*	2.380	−5.525
	(0.021)	(0.017)	(4.188)	(3.201)
Post times wage gap	−0.014	0.003	−5.625	−2.293
times negative shock	(0.031)	(0.026)	(10.262)	(7.357)
Post times wage gap	0.017	0.006	1.134	0.477
times positive shock	(0.035)	(0.027)	(10.175)	(4.914)
Linear combinations (p)				
Negative	0.762	0.216	0.766	0.308
Positive	0.572	0.244	0.734	0.289
Observations	391,104	683,443	391,197	683,443
Panel B: Women				
Post times wage gap	0.011	−0.036***	3.000	−5.718**
	(0.021)	(0.011)	(4.534)	(2.610)
Post times wage gap	0.011	0.039	1.091	5.065
times negative shock	(0.033)	(0.033)	(11.387)	(8.362)
Post times wage gap	−0.059	−0.006	−9.877	−0.218
times positive shock	(0.050)	(0.031)	(15.229)	(7.558)
Linear combinations (p)				
Negative	0.570	0.931	0.731	0.938
Positive	0.372	0.235	0.636	0.443
Observations	184,643	369,579	184,689	369,579
Panel C: Men				
Post times wage gap	−0.003	−0.035	1.623	−5.221
	(0.027)	(0.029)	(5.222)	(5.352)
Post times wage gap	−0.036	−0.039	−11.284	−11.376
times negative shock	(0.045)	(0.038)	(10.182)	(7.696)
Post times wage gap	0.076*	0.027	9.294	2.856
times positive shock	(0.039)	(0.034)	(9.227)	(5.872)
Linear combinations (p)				
Negative	0.402	0.032	0.358	0.037
Positive	0.070	0.764	0.285	0.624
Observations	206,461	313,864	206,508	313,864

Notes: Standard errors are in parentheses and are clustered at the magisterial district and the survey wave level. Columns (1) and (3) include only individuals in the labour force. Columns (2) and (4) include all adults. A negative shock is defined as rainfall below the 20th percentile of the historical distribution for a given district, while a positive shock is defined as rainfall above the 80th percentile. Two district municipalities are not included: Alfred Nzo DM and Bohlabela DM.
* p<0.1 ** p<0.05 *** p<0.01