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Firms and inequality when unemployment is high

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Abstract
How important are firms for wage inequality in developing countries where structural unemployment is high? Research focused on contexts close to full employment has suggested a substantial role of firms in labor market inequality. Using matched employer-employee data from South Africa, I find that firms explain a larger share of wage variation than in richer countries. I consider drivers of this, documenting first a higher productivity dispersion as found for other developing countries. Secondly, I estimate the separations elasticity by instrumenting wages of matched workers with firm wages, and I find a low separations elasticity. This generates a high degree of monopsony, and the correspondingly high estimated rent-sharing elasticity helps explain the important role of firm wage policies in inequality. Monopsony may be driven by higher unemployment, and regional heterogeneity provides suggestive evidence for this. Such firm-level competitive dynamics may exacerbate inequality in developing countries more generally.

Key words: inequality, firm wage premia, unemployment, monopsony
JEL: D31; J31; J42; J63; J64

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1 Introduction

How relevant are firm pay policies to wage inequality in contexts of high unemployment? How does this relate to monopsony power in the labor market? And how do these answers relate to findings from countries close to full employment? While a fast-growing literature has investigated the role of firms in explaining labor market inequality, much of the attention has focused on the US and a handful of European contexts, partly due to a paucity of matched employer-employee administrative data (Bonhomme et al. 2022; Card et al. 2018). This raises the question of whether we can extrapolate the findings of the literature to developing countries, especially when they are are characterized by unemployment or labor surplus; and whether unemployment may in fact exacerbate wage inequality through the channel of firm wage policies. To make progress on these questions, I provide the first estimates of the wage inequality accounted for by firm pay policies and the associated mechanisms in South Africa.

Using matched employer-employee tax data from 2011 to 2016 for the universe of South African formal sector workers, I show that the dispersion of firm wage premia is high. I follow the literature in decomposing earnings into firm and worker wage premia, after implementing a battery of validation checks (Abowd, Kramarz, and Margolis 1999; Kline, Saggio, and Sølvsten 2020; Lamadon, Mogstad, and Setzler 2022). I find that the firm wage premia explain 28% of the total wage variance. Including the sorting of high-wage workers to high-wage firms, firms explain more than a *third* of wage inequality in South Africa. The dispersion of firm wage premia is substantially higher than comparable estimates for other countries, and even more so when considering the raw variance rather than the proportion explained, given that South Africa is one of the most unequal countries in the world (World Bank 2020).

What explains the high dispersion in firm wage premia in South Africa relative to other, high income countries? An explanation involving imperfect labor market competition may be counter-intuitive under conditions of labor surplus, since one may expect firms to recruit unemployed workers at a low constant wage. Yet models of monopsonistic competition which incorporate on-the-job search suggest firms may still contribute substantially to wage dispersion, and in fact higher unemployment may exacerbate this (Manning 2003a). To guide the discussion, I set out a framework close to Card et al. (2018) where variation in firm wage premia is due to two sources: firm productivity dispersion and the firm labor supply elasticity (the key measure of monopsony power). A simple regression-based implementation of this framework explains about half of the dispersion in firm wage premia. Using the firm balance sheet information in these tax data, I provide evidence that indeed South Africa has high firm productivity dispersion compared to high-income countries, but actually more similar to other developing countries (Hsieh and Klenow 2009).

I then focus on the firm labor supply elasticity. I estimate this based on a variety of worker separations designs from the literature, including cross-sectional variation, productivity shocks, and instrumenting wages of matched workers with firm wages in an event-study of movers (Bassier, Dube, and Naidu 2022; Lamadon, Mogstad, and Setzler 2022; Webber 2022). My estimates of the firm labor supply elasticity are lower than comparable estimates from several countries (Sokolova and Sorensen 2021). Indeed, my framework, as in the literature, relates a lower firm labor supply elasticity to a higher firm wage dispersion. One important reason is that it mediates a higher pass-through of productivity dispersion to firm wage dispersion, since under a constant competitive wage firms would pay workers similarly regardless of firm productivity. I directly check this implication by separately estimating the pass-through (or rent-sharing elasticity), and correspondingly find this is towards the high end of the range in the literature. The firm labor supply elasticity also affects firm wage dispersion through other channels – such as heterogeneity in the elasticity itself – and I briefly discuss their relevance.

Finally I suggest that the low estimated firm labor supply elasticity may be related to the high unemployment rate in South Africa. When unemployment is high, there is less wage competition between employers, and workers are more reluctant to quit when paid poorly. Cross-regional correlations support this relationship, though are only tentative. If correct, South Africa's two world-ranking labor market features, unemployment and inequality, may be partially linked through a firm-based mechanism, whereby unemployment contributes to a low labor supply elasticity, which in turn drives up the firm wage dispersion.

An instructive comparison to the South African context is Brazil, which has high inequality and informality. Alvarez et al. (2018) show that firm wage premia dispersion accounts for a high proportion of total wage variance, and the pass-through of productivity to wages is also high. More generally, I discuss how the firm-level mechanisms I have identified in this paper, which link inequality and two typical developing country features (low formal employment and high firm productivity dispersion), may be part of the development process.[1]

While previous work in this literature has focused predominantly on high income countries, further work in low and middle income settings will hopefully shed more light on the mechanisms argued in this paper. Work on firm-based inequality generally requires matched employer-employee data, which is typically restricted to formal employment. I offer three lessons in this paper for focusing on formal employment in the context of high unemployment and informality. Firstly, in performing variance decompositions of firm and worker wage premia, a key validation test is that wage changes for workers moving from one firm to another are equal to the wage changes when moving in the opposite direction. I find that this test performs much worse when restricting to workers with a gap in formal employment (and better otherwise). The variation of wages explained by the corresponding estimated wage premia is also lower in this case (again, higher otherwise). This is consistent with the possibility that long unemployment or informality spells entail a penalty, which contributes to asymmetry in wage changes and biases the wage premia estimates.

Secondly, the exclusion of informal incomes from the wage variance decomposition leads to underestimates of the raw variance in firm wage premia, since these jobs generally have lower wages. The raw variance of wages due to firms is therefore likely larger in contexts of higher informality. Thirdly, my complementary analysis using survey data suggests that informal wage-workers (who constitute a large part of informal employment) may face similar competitive dynamics to formal wage-workers. Consistent with this, workers flow more from low-wage informal to higher-wage formal employment than in the reverse direction, and workers' wages decline as much as they rise when transitioning in opposite directions. The crude estimate of the firm labor supply elasticity is low and of the firm rent-sharing elasticity is high. This provides a tentative basis for applying the framework above beyond formal employment.

[1] To my knowledge, no papers have discussed the full thread of these links, or explored its implications for high unemployment settings. Several papers have showed the empirical links between firm wage dispersion and rent-sharing (e.g. Card, Cardoso, and Kline 2016; Card, Heining, and Kline 2013), and others between rent-sharing and labor market power (e.g. Kline et al. 2019; Saez, Schoefer, and Seim 2019). Hirsch, Jahn, and Schnabel (2018) have considered the link between labor market power and unemployment, but only in the context of time series cyclical unemployment in Germany.

After describing the data. Section 3 provides estimates of wage premia in South Africa, including several validation checks on identification and cross-country comparisons. Section 4 discusses reasons for the higher dispersion in firm wage premia relative to other countries, by laying out a framework, then focusing on the firm labor supply elasticity, and motivating its links to unemployment. I end with further discussion of the informal sector, and the relevance of firm-based inequality to the development process more generally.

2 Description of data

I use six years of matched worker- and firm-level data from South African administrative tax records between 2011 and 2016, made available through a confidential data-sharing agreement with South Africa's National Treasury and UNU-WIDER (National Treasury and UNU-WIDER 2020a; National Treasury and UNU-WIDER 2020b). A collection of papers describing and using this dataset appears in a special issue of the South African Journal of Economics in the first quarter of 2018. I describe in more detail my sample construction in Appendix B, including comparisons to nationally representative surveys and how my formal sector data relate to the informal sector.

The cleaned dataset used for my analysis consists of 8-9 million workers in each year, summarized in Table 1. The median real annual wage is stagnant, growing about 0.2% per year, compared to much faster growth at the 90th percentile of about 1.5% per year. This pattern of growth is consistent with trends based on publicly available tax tables (Bassier and Woolard 2021). Over a third of workers separate from firms each year, in line with findings for the same data by Kerr (2018). Close to half of the workers who separate go to other firms (E-E or Employment to Employment separations) and the rest are not employed in the following year (E-N or Employment to Non-employment separations).

I observe unique identifiers for workers as well as establishments. However, balance sheet information is only reported at the firm level, i.e. for all establishments belonging to the same firm. In the analysis below, "firm" wage premia would more accurately be named "establishment" wage premia (section 3); similarly, the estimated firm labor supply elasticity uses individual level separations defined at the establishment level (section 4.2). On the other hand, variation in value added is observed at the firm-level, not by establishment.

Overall, these administrative data contain no sampling error, are probably more reliable for wages than surveys,[2] and provide a unique opportunity to track a panel of workers at their firms over an extended period.[3] However, this dataset is not representative of all workers in South Africa. My sample may be better described as workers at sizable formal firms, since I focus on firms with more than 20 workers for reliable estimation of the wage premia. Importantly, informal, unreported work such as domestic workers and informal traders are excluded, which together comprise a third of all employment, and have relatively lower incomes and conditions. Despite these caveats, the data still reflect the actual incomes of over half of all workers in South Africa for six years.

Workers' unemployment spells are not directly observed in these tax data. In order to study the links with unemployment, I therefore merge in survey data at the region-level. I estimate unemployment by local municipalities, of which there are 226 in South Africa, using the 2011 National Census for precision (Statistics South Africa 2011). I measure unemployment as the unemployment to population ratio, a broad measure which circumvents the ambiguous classification of informal sector jobs. As a secondary measure of unemployment, I use the tax data to estimate duration of unemployment through gaps between employment spells. However, this is imprecise since the tax records are annual.

3 Dispersion in wage premia

In this section, I study the dispersion in wage premia for the South African labor market. I begin by laying out the estimation method and associated validation checks, then I present the variance decomposition of wage premia, and end with comparisons to other estimates in the literature.

[2]Surveyed wages are typically dependent on respondents remembering exact figures across many months (including once-off payments like annual bonus) in the right definitions (e.g. net or before tax) and being willing to give up socially private information.

[3]There are no other matched employer-employee dataset available in South Africa. The National Income Dynamics Survey is the other possibility for panel data analysis for individuals in South Africa, but suffers from small sample size and is only collected every other year.

3.1 Estimation and validation of wage premia

The idea that firms have specific wage premia was first empirically investigated by Abowd, Kramarz, and Margolis (1999) or AKM, followed by several papers since then (e.g. Card, Heining, and Kline 2013; Song et al. 2018). I follow these papers in estimating firm and worker wage premia using the AKM wage equation, which imposes that a worker's wage can be additively decomposed into "firm effects" ϕ_j (used interchangeably with "firm wage premia" in this paper), "worker effects" α_i, and an error term as shown in equation 1. The outcome is log annualized wages for individual i in firm j for year t. To account for life cycle and time effects, I control for X_{ijt} as up to a cubic in age, as well as year fixed effects.[4] All analysis is restricted to the largest connected set of firms.[5]

$$ln(wage_{ijt}) = c + \sum \alpha_i + \sum \phi_j + X_{it}\rho + \upsilon_{ijt} \tag{1}$$

Intuitively, worker effects α_i are the portable component of the worker's wage, the part that the worker is paid no matter which firm she is at. Firm effects ϕ_j are added to the wage of all workers currently at firm j, regardless of their worker effect. Identification of the firm effects in this setup relies on movers, that is, workers who switch between firms. Hull (2018) illustrates this with a simple two firm, two period case: assuming parallel trends (i.e. the counterfactual wage growth of a mover is that of a stayer) and impersistence (i.e. the mover's wage at the new firm is the same as if she had always been there), then the firm 2 effect is just a weighted average of the wage gain experienced by movers from firm 1 to firm 2, and the wage loss experienced by movers from firm 2 to firm 1. The additive structure of AKM imposes that the wage gain and loss are equal.

There are a number of tests to evaluate whether the structure imposed in equation 1 is appropriate. The most well-known follows Card, Cardoso, and Kline (2016), presented in Figure 1 Panel A as a non-parametric justification for the AKM structure. The figure depicts the average wages of workers before and after switching firms. The sample is restricted to those

[4] Following Card, Cardoso, and Kline (2016), I exclude the linear term in age, since age and year fixed effects are perfectly co-linear, and normalize the squared and cubic terms by age 40.

[5] Firms A, B and C are connected if the same worker is observed at A and B, and a (potentially different) worker is observed at both B and C. This enables comparison between wage premia of the firms, based on the differences in wages experienced by movers.

continuously employed over the period, for three years at their original firm preceding their move, and three years after their move. For both the original and destination firms, workers are classified by quartiles in the co-worker firm wage distribution, i.e. leaving out the wage of each worker.

In the three years before the switch, wages for movers across the distribution are stable, which is consistent with the parallel trends assumption. There is little evidence of a substantial "Ashenfelter Dip", i.e. the possibility that workers systematically experience a negative event just prior to switching firms, which registers as below-average wages in $T-1$ and *causes* them to switch firms, thus spuriously indicating a firm wage gain on switching. The stability of wages after the move supports the impersistence assumption, such that the average wage of workers directly after moving is similar to the average wage at the same firm 2 years later.

Figure 2 Panel A presents evidence in favor of the assumption in the AKM regression that wage gains and losses across bilateral flows between firms are equal. As in Card et al. (2018), I plot the wage change for quartile i to j workers on one axis against the quartile j to i change on the other axis. These changes are close to symmetrical, with the wage changes lying along the 45 degree line. Note the *large magnitude* of the average change in wages associated with firm transitions for the *same* worker: the change in wages associated with a one-quartile transition is 15-20% in wages, and with two-quartile transitions is 40-60% – by contrast, the analogous figure for Portugal shows two-quartile differences of 25-30% (Card et al. 2018). The variance decomposition in the next section quantifies the importance of such wage differences in the full wage distribution.

The AKM regressions rest on several other assumptions, many of which can be tested. I take these up in Appendix C, including checking for patterns in regression residuals, limited mobility bias, and compensating differentials (Abowd, McKinney, and Schmutte 2019; Bonhomme et al. 2022; Lamadon, Mogstad, and Setzler 2022). I find that the tests are roughly satisfied. To help address remaining concerns of endogeneity, I also present estimates from a set of firms which closed down, arguably leading to more exogenous worker moves. As recommended by Kline, Saggio, and Sølvsten (2020) or KSS, I use as my primary set of estimates their leave-out estimator which corrects for the mismeasurement of the fixed effects.

I highlight two lessons for estimating AKM regressions particularly regarding developing country contexts where formal sector matched employer-employee data exclude a large part of the labor force. Firstly, in principle the AKM statistical model and validation tests should hold even when a significant proportion of transitions is not observed; for example in the case of out-migration as in studies of US states (e.g. Lachowska et al. 2020). However, the estimation of firm wage premia is methodologically more reliable when based off *continuously employed* movers in the matched sample, i.e. the observed formal sector. In contexts with high unemployment and informality, like South Africa, many observed transitions within the formal sector follow relatively long gaps of more than a year.[6] Such gaps may well be penalized by hiring firms, violating the additive structure of the AKM wage premia. Indeed, Figure 2 Panel B shows that the wage losses are systematically greater than the wage gains for workers who have such a gap, leading to far less symmetry in wage changes than for workers who are continuously employed as in Panel A. Such gaps, whether due to unemployment or informal sector employment, are not considered in standard AKM estimation, and could only partially be controlled for by duration of the gap (since this again imposes an assumption on the shape of the non-formal employment penalty across time, worker types, and firms).

Secondly, the exclusion of the informal sector will affect the variance decomposition of the wage premia. The informal sector wage distribution is substantially lower than the formal sector wage distribution, though plausibly with similar wage-setting patterns to the above for informal sector wage-workers. This will likely increase the raw variance of firm wage premia, meaning that estimates based on formal sector data will underestimate the the contribution of firms to wage inequality, particularly compared to higher income countries which do not have large informal sectors. Section 5.1 provides further discussion on this, including rough calibrations of the magnitude of this effect on my estimates.

This subsection has motivated the simple framework of assigning firm-specific wage premia. The additive AKM structure passes several validation tests recommended in the literature, yet with some important differences related to South Africa's large unemployment and informal

[6] Calibrating to QLFS data (Statistics South Africa 2010-2015), the monthly job-finding rate $\lambda \approx 0.056$. The implied frictional unemployment duration is about $1/\lambda = 18$ months, which is plausible in South Africa. Of course the mean job-finding rate and duration may diverge strongly from the median.

sector characteristic of a developing country. Next I demonstrate that these firm wage premia play an important role in the South African labor market.

3.2 Variance decomposition of wages

Firm wage premia in South Africa explain a high proportion of total wage inequality. Table 2 summarizes the variance decomposition of wages. Column 1 presents the standard AKM set of wage premia: of the total wage variance, the variance in firm wage premia accounts for 29%, the variance in worker wage premia accounts for 44%, and the covariance between the firm and worker wage premia accounts for an additional 8%. Other terms, such as age and year effects, account for 7%. The R-squared in this baseline regression is 0.88, suggesting the additive AKM model fits the data well. My preferred set of estimates corrects for limited mobility bias using the KSS estimator. Column 2 shows the percentage variance explained by firm wage premia is similar (28%), as for the covariance (8%) and other terms (7%), but the variation explained by worker wage premia is lower (37%) and by the residual in turn higher (19%).[7] This suggests that, under a counterfactual of no firm wage premia, wage inequality would be 36% lower (28% plus 8%).

As discussed earlier, the specification assumptions may be more plausible when using the subsample of firm closings. Column 3 shows a very similar percent variance explained by firm wage premia (29%). The other components change somewhat, notably the sorting term declines, which may indicate the relevance of endogenous transitions to where workers locate in the full sample (as Bassier, Dube, and Naidu (2022) discuss, this does not affect the assumptions required for AKM). The percent variance explained by firm wage premia is also similar when including firms of any size (25%, with 49 million observations), or when demeaning by industry (26%).

To demonstrate the relevance of unemployed workers to the estimation of these firm wage premia, I restrict to the subsample of workers with a gap in observed formal employment (column 4). The firm and worker components are lower for workers with gaps (24% and 28%

[7]The KSS correction has little effect on the estimated percentage of variance explained by firm wage premia, in contrast with Bonhomme et al. (2022). However, this is consistent with their caveat that limited mobility bias is smaller in longer panels, such as mine of 6 years.

respectively), compared to the full sample. A key difference is a larger proportion explained by the residual (30% compared to 19% for all workers), which indicates a worse fit of the specification to the data and is consistent with unaccounted-for terms in Equation 1 associated with a gap in formal employment. On the other hand, when I restrict to the subsample of workers who are recorded as working full-time every year to avoid workers with employment gaps, the variance accounted for by the residual drops down to 9% (column 5). In this full-time subsample, the firm wage premia term rises to 33%.[8]

The covariance term in Table 2 implies that there is substantial "sorting", meaning that workers with a high worker component in wages are disproportionately located in firms with high firm wage premia. This is visualized in Appendix Figure A1, where I plot the distribution of worker wage premia for each decile of firm wage premia. Still, *some* workers with low worker premia are in high paying firms, which is a key requirement of this AKM framework where there exist "good" and "bad" jobs available to the same worker.[9] As an aside, the figure also shows that nearly a quarter of workers are located at the highest paying 10% of firms, which hints at the dynamics explored in section 4.2 on the firm labor supply elasticity.

Another way of expressing the importance of the role of firms in wage inequality is through a comparison of average wage components by decile of income (Figure 3). The distribution of firm wage premia substantially increases between-decile income inequality compared to just considering invariant worker characteristics (i.e. worker wage premia). Comparing deciles 1-4 to deciles 5-8 of unconditional income, the proportion of the income gap explained by the average differences in firm wage premia is *greater* than the proportion explained by average differences in worker wage premia.[10] This is a noteworthy finding for the South African literature which focuses on skills in explaining inequality, given that the worker fixed effect includes all invariant worker-specific characteristics such as education (see review in Leibbrandt,

[8] I do not use this as my preferred set of estimates since it is a less representative sample, with 25 million observations compared to 42 million in the full sample. Note the selection on full-time workers may contribute to the decline in the sorting term.

[9] Another aspect of sorting is the "match" effects that may come about, for example if high premia workers produce more when at high premia firms as in the model of Lamadon, Mogstad, and Setzler (2022). One way of testing this is to compare the R-squared from the AKM model (0.88) to the R-squared from a fully interacted "jobs" regression which will include match effects (0.94). While there is a difference, it is relatively small and suggests marginal importance as in Card, Cardoso, and Kline (2016).

[10] Average worker premia however play a dominant role for gaps with the top two deciles.

Ranchhod, and Green 2018).

In sum, firm wage premia in South Africa explain over a quarter of the total wage variance in sizable formal sector firms, and over a third when accounting for sorting.

3.3 Comparison to estimates in other countries

How does this variance decomposition in South Africa compare to estimates for other countries? As highlighted by the recent review of Bonhomme et al. (2022), care needs to be taken in selecting comparable estimates since not correcting for limited mobility bias can overestimate the share explained by firm wage premia and underestimate the share explained by sorting.[11] While the difference between my uncorrected (AKM) and corrected (KSS) estimates in Table 2 are negligible, Bonhomme et al. (2022) show that the corrections make a substantial difference in other settings. In Figure 4, I plot the 37 estimates from 11 countries compiled by Bonhomme et al. (2022), along with my own, and with a focus on the most comparable estimates.[12]

My estimate for the share explained by firm wage premia in South Africa (28%) is well above the comparable KSS estimates for Austria, Italy, Norway, Sweden, and USA, which range between 6% and 16% (Panel A). When considering uncorrected estimates, my estimate is towards the upper part of the distribution (85th percentile), though this comparison is not as informative given these estimates are upwardly biased in complex ways.

The role of firms in South African wage inequality is even more prominent when considering the raw variance rather than the share explained, since South Africa has one of the highest rates of overall inequality worldwide (Panel B). In this compiled list of estimates, South Africa has by far the highest wage variance of 1.32, where the closest is USA in Song et al. (2018) at 0.92. The raw variance in South Africa (0.37) is therefore much larger than other estimates, whether considering the comparable KSS estimates (maximum of 0.03) or the upwardly biased

[11] The literature focuses on the role of firms in wage inequality, such that worker wage premia are only of interest as they relate to sorting. Bonhomme et al. (2022) do not include the estimated share of variance explained by worker wage premia in their cross-country review.

[12] The construction of my panel is very similar to the harmonized estimates from Bonhomme et al. (2022): annual earnings panels, estimated over 6 years, and with the worker's highest earnings employer taken for each year. A source of difference is that they use a minimum earnings cutoff to address part-time employment, whereas I annualize earnings. I also include a minimum firm size restriction, though for the KSS estimates Bonhomme et al. (2022) show very little sensitivity to this (my estimate of the variance explained by firm wages is 25% when dropping this threshold).

estimates (maximum of 0.23).

Regarding sorting, my estimates are more in line with other countries (Appendix Figure A2). The share explained by sorting in South Africa is within the range of estimates for other countries. The raw variance due to sorting (0.14) is indeed higher than the other KSS estimates (maximum of 0.05), and towards the upper part of the range of uncorrected estimates (note these are *downwardly* biased).

Overall, my estimates for the firm wage dispersion in South Africa stand out, even before considering the likely underestimation due to excluding the informal sector. I focus on this for the rest of the paper, leaving discussion of variance due to sorting and worker wage premia to future work. A key difference between South Africa and the estimates for the countries reviewed above is the level of development, with the comparable KSS estimates all coming from high income countries, and similarly for the rest of the estimates (except Brazil). In the next section, I provide some evidence in explaining the dispersion in firm wage premia, including links to structural features of South Africa shared by other less developed countries.

4 Reasons for the high firm wage dispersion

In this section, I discuss explanations for the higher dispersion in firm wage premia in South Africa as compared to other, mostly high income countries. I begin by setting out a simple framework to guide the discussion of the sources of firm wage dispersion, and provide some evidence on why these sources may contribute more in South Africa. I focus on one mechanism, a low firm labor supply elasticity, and discuss its link to high unemployment.

4.1 Framework

The most popular motivations for the prevalence of firm-specific wage premia involve imperfect competition, such as firm monopsony power based on taste heterogeneity (Card et al. 2018; Lamadon, Mogstad, and Setzler 2022) or search frictions (Manning 2003a). Here I use a partial equilibrium setup close to Card et al. (2018), as well as Dickens, Machin, and Manning (1999), with more details provided in Appendix D.1.

Firm j faces downwards sloping firm-specific product demand parameterized by η, and has exogenous productivity for each worker type i equal to a firm term T_j multiplied by a worker type term A_i. For example, production is given by $Y_{ij} = \frac{\eta}{\eta-1} A_i T_j N_{ij}^{1-1/\eta}$ for $N_{ij}(w_{ij})$ the number of workers of type i at firm j. Firms maximize profit by setting the wage w_{ij} for each worker type i, subject to an upwards sloping firm labor supply constraint with elasticity ε_j:

$$\max_{w_{ij}} \pi_{ij} = \frac{\eta}{\eta - 1} A_i T_j N_{ij}^{1-1/\eta} - w_{ij} N_{ij} \quad \text{subject to } N_{ij} = w_{ij}^{\varepsilon_j} \tag{2}$$

Setting log marginal revenue product equal to log marginal cost of labor for each firm j, wages are given by:

$$ln(w_{ij}) = \frac{\eta}{\eta + \varepsilon_j} ln(A_i) + \frac{\eta}{\eta + \varepsilon_j} ln(T_j) + \frac{\eta}{\eta + \varepsilon_j} ln(\frac{\varepsilon_j}{1 + \varepsilon_j}) \tag{3}$$

While there are many other factors relevant to wages, this framework allows me to focus on the role of firms, as in Card et al. (2018) and Dickens, Machin, and Manning (1999). Variation in firm wage premia ϕ_j is due to two sources: firm productivity dispersion and the firm labor supply elasticity.[13] Without taking the functional form too seriously, the framework suggests that variation in firm wage premia has a positive relationship with variation in firm productivity, an inverse relationship with $\bar{\varepsilon}_j$ (the average of ε_j) as it mediates the pass-through of each term, and a positive relationship with variation in ε_j. Below I unpack these relationships more. As I discuss later, the R-squared from a simple regression of the estimated firm wage premia on log value added (a proxy for $ln(T_j)$) is nearly a quarter, and together with market-specific fixed effects accounts for half of the total variation in firm wage premia in South Africa.

A useful baseline case is a constant firm labor supply elasticity $\bar{\varepsilon}_j = \varepsilon_j$, such that $\alpha_i = \frac{\eta}{\eta+\bar{\varepsilon}_j} ln(A_i)$ relates to the worker-specific effect, $\phi_j = \frac{\eta}{\eta+\bar{\varepsilon}_j} ln(T_j)$ relates to the firm-specific component of wages, and $c = \frac{\eta}{\eta+\bar{\varepsilon}_j} ln(\frac{\bar{\varepsilon}_j}{1+\bar{\varepsilon}_j})$ relates to the constant. This is an additive model of wage-setting consistent with the Equation 1 statistical model of wage premia in Abowd,

[13]Following Card et al. (2018) (the leading model in the literature on which I base my comparisons), I do not focus on η. I also follow Card et al. (2018) in not modeling worker sorting, leaving this important question to future work. My focus on firm wage premia rather than sorting also follows from Section 3.3, where South Africa stands out in firm wage premia dispersion.

Kramarz, and Margolis (1999).[14] In particular, $var(\phi_j) = (\frac{\eta}{\eta+\bar{\varepsilon}_j})^2 var(ln(T_j))$, highlighting the positive relationship with $var(ln(T_j))$ and negative relationship with $\bar{\varepsilon}_j$.

Firm productivity T_j

Several papers highlight that there is a greater dispersion in firm productivity in developing countries, and this leads to higher allocative inefficiencies (Alfaro, Charlton, and Kanczuk 2009; Hsieh and Klenow 2009; Hsieh and Olken 2014). In my framework, higher firm productivity dispersion also leads to greater dispersion in firm wage premia. Indeed in South Africa, this relationship specified in Equation 3 is supported by a strong linear relationship between firm productivity, variously defined, and firm wage premia (see Appendix F).

How does the productivity dispersion in South Africa compare to other countries? I show a variety of estimates for South Africa in Appendix Table A1. In Appendix Figure A3, I show that the productivity dispersion in my data is higher than comparable estimates for 18 out of 20 other countries drawn from Bartelsman, Haltiwanger, and Scarpetta (2013), Bartelsman and Wolf (2017), and Hsieh and Klenow (2009).[15] This uses the standard deviation in log total factor productivity (TFP), but other measures provide a similar picture – for example, Bartelsman and Wolf (2017) document an inter-quartile range in labor productivity across countries generally between 0.5 and 1, while my comparable estimate is 1.01 in South Africa. In another study, Kreuser and Newman (2018) also note high dispersion of within-sector firm productivity dispersion in South Africa. Similarly to the estimates regarding firm wage premia, the inclusion of informal sector firms would likely increase the estimated dispersion. Overall, this suggests high dispersion in firm productivity is an important part of why dispersion of firm wage premia

[14] In an abuse of notation for the sake of readability, I use ϕ_j in both Equation 1 and here to refer to the firm wage premia. The latter imposes a functional form on ϕ_j, while the former is purely a statistical representation of a firm indicator term. In my analysis, I make use of the estimated firm wage premia from section 3. The same applies to α_i. Additionally, insofar as there is variation in ε_j across firms, α_i has a firm-specific component too. However, the validation checks in 3 suggest that the firm or match component of this term is relatively small. Similarly for c, which may be absorbed into ϕ_j and is discussed later.

[15] I attempt to make the estimates as comparable as possible. Productivity is measured across all sources as total factor productivity (TFP) within each industry, i.e. value added residualized by a regression on 4-digit industry specific terms of the mean, capital, labor, and material costs, and restricted to the broad manufacturing sector. In a review, Syverson (2011) notes that despite the voluminous literature on productivity measurement, fortunately "when studies have tested robustness directly, they typically find little sensitivity to measurement choices." In Appendix Table A1, I show my estimates have little sensitivity to industry disggregation or firm size thresholds, though dispersion in total factor productivity is generally lower than labor productivity (as found elsewhere, e.g. Bartelsman and Wolf 2017).

is high in South Africa.

The other high-dispersion estimates generally also concern developing countries; for example, Hsieh and Klenow (2009) show a standard deviation in log TFP of 0.49 for USA, compared to 0.67 for India and 0.63 for China (my estimate for South Africa is 0.64). The greater variation in productivity in developing countries is potentially driven by diverse factors such as managerial talent, average labor quality, investment, spillovers, competition and input markets (Bloom and Van Reenen 2010; Syverson 2011). The further documentation of the productivity dispersion and its sources in South Africa and elsewhere is an important avenue for future work.

Firm labor supply elasticity ε_j

The parameter ε_j is crucial in this framework, as it measures the degree of frictions in the labor market and parameterizes firms' monopsony power. It affects the variance of firm wage premia through its level value and variability. Firstly, in terms of the level value, the pass-through from each term in Equation 3 to the variance in wages is mediated by the average firm labor supply elasticity $\bar{\varepsilon}_j$. In particular for the base case where $var(\phi_j) = (\frac{\eta}{\eta+\bar{\varepsilon}_j})^2 var(ln(T_j))$, the effect of productivity dispersion $var(T_j)$ on firm wage premia dispersion $var(\phi_j)$ is mediated by $\bar{\varepsilon}_j$. The intuition is that firms with higher marginal revenue product T_j gain more from employing more workers; when $\bar{\varepsilon}_j$ is lower, these higher productivity firms need to raise wages more in order to attract the same number of workers than if $\bar{\varepsilon}_j$ was higher, which increases the pass-through of productivity differences to wage differences. A lower $\bar{\varepsilon}_j$ can increase the pass-through of firm productivity variance substantially: $\bar{\varepsilon}_j = 6$ compared to $\bar{\varepsilon}_j = 1.5$ implies a variance in firm wage premia *two-thirds* lower, given the *same* variance in productivity.[16]

Secondly, the firm labor supply elasticity ε_j itself could vary, for example if frictions differ by local labor market, by informal versus formal sector, or even by firm. How would this affect the variance in the wage given by Equation 3? Second order Taylor approximations suggest that such heterogeneity may have very limited effect, whether through the pass-through coefficient

[16] Note the squared term in $var(\phi_j) = (\frac{\eta}{\eta+\varepsilon_j})^2 var(ln(T_j))$. These values of $\bar{\varepsilon}_j$ are illustrative, though in line with the literature and my estimates below. I assume a firm-specific product demand elasticity of 5, which is in the range of Card et al. (2018) who calibrate using values between 3 and 10. Of course, one should not take the functional form of Equation 3 too seriously, and rather treat this as suggestive of the importance of $\bar{\varepsilon}_j$.

$\frac{\eta}{\eta+\varepsilon_j}$ or the third term $\frac{\eta}{\eta+\varepsilon_j}ln(\frac{\varepsilon_j}{1+\varepsilon_j})$ (see Appendix D.1). As such, I focus below on $\bar{\varepsilon_j}$, with brief comments on $var(\varepsilon_j)$.

Although not modeled explicitly in Equation 3, note that other constraints on wage-setting may further increase the variability in wages. Regarding even a constant firm labor supply elasticity $\bar{\varepsilon_j}$, Manning (2020, p.9) discusses how it is unclear "whether employers exercise this monopsony power as a simple profit-maximizing model would suggest or whether other factors act as a constraint". Constraints include fairness norms (Dube, Giuliano, and Leonard 2019; Saez, Schoefer, and Seim 2019), national wage-setting (Hazell et al. 2021), and union premia (Dodini, Salvanes, and Willén 2021). Once again, if $\bar{\varepsilon_j}$ serves as a reference point for these constraints, then a lower $\bar{\varepsilon_j}$ will increase the contribution of varying use of potential monopsony power to the variance of wages.

In sum, this framework suggests greater dispersion in firm wage premia is due to greater dispersion in firm productivity, as well as a lower (and more heterogeneous) firm labor supply elasticity ε_j. Above I provided some evidence on a greater dispersion in firm productivity in South Africa. In the next subsection, I estimate the firm labor supply elasticity $\bar{\varepsilon_j}$ in South Africa, and show that it may be particularly low, thereby contributing to the high firm wage dispersion.

4.2 Monopsonistic wage-setting: The firm labor supply elasticity

Estimation framework

Evidence for an upwards-sloping firm labor supply elasticity has grown rapidly over the last decade (for reviews, see Ashenfelter et al. 2022; Card 2022; Manning 2020). I estimate the firm labor supply elasticity from worker separations responses to their wage (denoted ε_{sep}), an approach widely used in the literature (e.g. Bachmann, Demir, and Frings 2022). The intuition is that a lower quit response of workers to a cut in their firm's wage indicates a less competitive market, and more monopsonistic wage-setting power. The basic specification is shown in Equation 4, where s_{ijt} denotes a separation of worker i from firm j in year t, and w_{ijt} is her corresponding wage.

$$ln(s_{ijt}) = \alpha + \varepsilon_{sep} ln(w_{ijt}) + \Gamma X_{ijt} + \nu_{ijt} \tag{4}$$

Following Manning (2003a), the estimated firm labor supply elasticity (ε_{LS}) can either be computed as double the separations elasticity, $\varepsilon_{LS} \approx -2 \cdot \varepsilon_{sep}$, or as a combination of elasticities with regard to other types of transitions (Equation 5, where the weights θ are the proportion of all hires that are from employment).[17]

$$\varepsilon_{LS} = -(1+\theta)\varepsilon_{EEsep} - (1-\theta)\varepsilon_{ENsep} - \varepsilon_{EErecruits} \tag{5}$$

In the ideal experiment, wages are exogenously assigned to workers and their different separation responses give the separations elasticity. In my first empirical strategy (OLS), which is comparable to much of the literature, I use an OLS regression with worker's wage as the primary regressor, and the controls indicated by X_{ijt} include the worker type (i.e. the worker wage premium estimated in the AKM regression), as a means of capturing invariant worker characteristics of the wage, as well as time effects. Any unobserved heterogeneity which influences both the wage and the separation rate, such as if workers who are paid highly have access to better outside options, would violate the assumed conditional exogeneity of the wage.

As a second strategy (First Difference), I use separations responses to productivity shocks which affect the firm average wage. I take the first-differenced change in firm value added per worker as an instrument for the first-differenced firm average wages. I compare this change in wages to the first-differenced change in the separation rate of workers at the firm. In contrast to the OLS strategy, this is a firm-level regression which allows me to trace out the firm labor supply curve through isolating shifts in the firm-specific marginal revenue curve.[18] This identification strategy also uses variation from within each firm across time rather than from the

[17]Elasticities for other types of transitions are estimated analogously to Equation 4. That is, replace s_{it} in equation 4 with y_{it}, where y_{it} indicate any separation as in equation 4 (yielding ε_{sep}), or employment to employment separations (yielding ε_{EEsep}), or employment to non-employment separations (yielding ε_{ENsep}), or the recruitment elasticity from employment (yielding $\varepsilon_{EErecruits}$).

[18]Studies which use firm shifters in firm revenue include Kline et al. (2019) who use patents, Berger, Herkenhoff, and Mongey (2022) who use tax changes, and Garin, Silvério, et al. (2019) who use export shocks. My estimates are conceptually similar, though not as well-identified since I use any statistical change in firm value added per worker rather than a policy induced one. Lamadon, Mogstad, and Setzler (2022) similarly use statistical variation.

cross-section of workers.

As a last strategy (Movers), which in my view is the most credible but has fewer comparable estimates in the literature, I estimate the separations elasticity using the matched event-study of worker movers following Bassier, Dube, and Naidu (2022) (see Appendix E for details). I track similar workers from the same firm who then separate in the same year to different firms. Here, the identification assumption is that the firm average wage at the new firms are random, conditional on the workers' respective histories, and so the workers' separation rates from these new firms are well-identified — an instrumented difference in differences specification for equation 4.

Estimates of the firm labor supply elasticity

As *prima facie* evidence of an upwards-sloping firm labor supply elasticity, there is a strongly linear relationship between higher firm wages and lower worker separation rates (Figure 5). A similar relationship appears using the Movers design, between differenced firm wages and differenced separations (Appendix Figure E2).

I estimate a low firm labor supply elasticity across the three strategies, which is consistent with the high firm wage dispersion found earlier. Table 3, column 1, shows a separations elasticity of -0.31 from the OLS regression with controls for worker type, which yields a firm labor supply elasticity of 0.86. Adding industry by region market fixed effects, which may also proxy for potentially different amenities by industry and location, decreases the combined firm labor supply elasticity to 0.77 (column 2). The estimation strategy using firm-level first-differences gives similar results, with an estimated separations elasticity of -0.32 and a firm labor supply elasticity of 0.74 (column 3). The movers event-study strategy yields higher estimates, with a separations elasticity of -0.79, and produces a firm labor supply elasticity of $\varepsilon_{LS} = 1.6$ (column 4, with further results reported in Appendix E).[19]

This range of estimates for the firm labor supply elasticity suggests that it is lower in South

[19]The Appendix Table E1 shows the full range of estimates for each of these specifications, including the different transition elasticities to the wage. Note however that ε_{EEsep} contains some measurement error associated with missing formal sector to informal sector employment transitions. As expected, ε_{EEsep} are all greater in magnitude than ε_{sep}, but ε_{ENsep} are lower in magnitude. The movers regression just uses $\varepsilon_{LS} \approx -2 \cdot \varepsilon_{sep}$ since the strategy is not amenable to estimating ε_{ENsep}, following Bassier, Dube, and Naidu (2022).

Africa than other, especially high-income, settings. As in the firm wage premia literature, comparisons are tricky: a comprehensive meta-analysis by Sokolova and Sorensen (2021) finds large systematic differences due to statistical methods. The authors report best-practice estimates for the separations-based approach between 6.4 and 9.9, based on 29 published studies from 9 countries.[20] The movers strategy estimate is also low compared to the only other comparable estimate of 3 for Oregon, USA (Bassier, Dube, and Naidu 2022).

Implications for wage dispersion

As discussed in subsection 4.1, the firm labor supply elasticity affects firm wage dispersion through at least two channels.

One channel is that the pass-through of productivity increases when the firm labor supply elasticity is lower, as suggested above.[21] There is a substantial literature estimating this pass-through or rent-sharing elasticity for several countries, with estimates which broadly range from 0.05 to 0.15 (see review in Card et al. 2018). I follow this literature to estimate the rent-sharing elasticity for South Africa, and provide details in Appendix F. In brief, my main specification follows Card, Cardoso, and Kline (2016) in a cross-sectional regression of estimated firm wage premia from section 3 on log firm value added per worker. I find a pass-through or rent-sharing elasticity of 0.14, which is towards the upper end of the comparable range reported above, and is robust to different measures of firm quasi-rents (profit per worker and estimated total factor productivity) and controls (year, industry and location). As an alternative specification, I use the panel and regress the differenced log firm average wage on the differenced log firm value added per worker. The estimated rent-sharing elasticity is 0.17, which includes fixed effects

[20]The authors kindly shared their dataset of estimates with me, allowing me to narrow the estimates to those most comparable to mine. Restricting to peer-reviewed estimates based on worker separations, my OLS and first-differenced estimates are in the 24th percentile; restricting further to those published in top journals only one out of 10 studies finds lower estimates than me, i.e. Dube, Lester, and Reich (2016), which is a minimum wage sector-wide shock not comparable to firm-level estimates. Top journals are defined by the authors, as top 5 economics general interest journals or the Journal of Labor Economics. All estimates are from high income countries, except one (Brazil).

[21]This is the case in the framework above, as well as across a number of other models (Card et al. 2018; Lamadon, Mogstad, and Setzler 2022; Manning 2003a). See Appendix F. It is worthwhile estimating the rent-sharing elasticity separately, rather than using calibrations, since the pass-through from productivity to wages may have a different functional form to my framework, and is also governed by several constraints. For example, collective bargaining or fair wage considerations may substantially alter the rent-sharing elasticity predicted purely from the firm labor supply elasticity, meaning there is no one-to-one relationship between the two.

for industry by location to isolate firm-specific shocks from market level shocks. In sum, the low firm labor supply elasticity estimated above corresponds with a (separately estimated) high pass-through channel which contributes towards higher dispersion in firm wage premia.

I do not provide direct evidence on the second channel, heterogeneity in the firm labor supply elasticity or in the constrained use of potential monopsony power, and instead I make two remarks. Firstly, it seems likely that variation in the pass-through coefficients and third term in Equation 3 exists. As an illustration, returning to the example of union constraints, I show in Appendix Table A3 that firms with higher union density have a cross-sectionally higher pass-through coefficient or rent-sharing elasticity, and this is robust to controls for worker quality, industry and location. Secondly, it seems variation in these terms are important sources of firm wage dispersion, measured in terms of explanatory power. A simple regression of the estimated firm wage premia on log firm value added yields an R-squared of 0.22. Adding either market-specific coefficients on log value added or market-specific constants increases the R-squared to 0.46, and adding both increases it to 0.5.[22] Of course there is undoubtedly much else driving this variation, including an entirely different functional form to Equation 3, and so this only motivates the possible importance of these sources of dispersion under the parsimonious framework above.

In this subsection, I estimated a firm labor supply elasticity that is low compared to other countries, with corresponding implications for a high pass-through rate leading to high firm wage dispersion. The next subsection poses a possible reason for this low firm labor supply elasticity – high unemployment.

4.3 Monopsony and unemployment

Motivation

Why does South Africa have a low firm labor supply elasticity? A partial explanation arises from the clear theoretical link with South Africa's high unemployment rate. For example, search models such as in Burdett and Mortensen (1998) provide a monotonic relationship be-

[22]Note that measurement error in log value added as an imperfect proxy for productivity will drive down the R-squared. This also does not account for any firm-specific characteristics besides log value added. Market is defined as industry by location cells.

tween lower job offer rates λ (indicating a lower ε), and higher steady-state unemployment, $1-\frac{\lambda}{\delta+\lambda}$. More generally, when unemployment is high, workers may have fewer forthcoming wage offers, and therefore be reluctant to quit in response to a wage cut. And since firms are able to draw more on the unemployed, they have less wage competition with other firms, and they can mark down wages further.

Equation 5 above suggests that this link is valid for any source of unemployment, whether structural in nature or frictional. Consider setting $1-\theta$ (the proportion of hires from unemployment) to the unemployment rate u, which implies that hires are drawn at random from the available labor force. Consider also that the value of the lowest firm wages may be sufficiently above the value of unemployment, that changing the wage does not induce more exit from unemployment. This suggests the elasticity of separation to non-employment may be close to zero, $\varepsilon_{ENsep} \approx 0$, and similarly for the elasticity of recruits from employment compared to non-employment, $\varepsilon_{EErecruits} \approx 0$. Substituting these values into equation 5, the firm labor supply elasticity can be written succinctly in terms of the unemployment rate and the employment to employment separations elasticity, $\varepsilon_{LS} = -(2-u)\varepsilon_{EEsep}$. That is, the firm labor supply elasticity decreases as the unemployment rate increases (note $\varepsilon_{EEsep} < 0$).

In practice, ε_{ENsep} can be substantial in magnitude (see Appendix Table A2), E-N transitions in the formal sector data may in reality include formal to informal sector transitions, and firm hires are likely to be disproportionately drawn from the employed. The subtraction of u may be better thought of as an approximate discounting of a labor supply elasticity based on ε_{EEsep}, to account for the idea that even if a formal sector firm's wage was decreased, the other option (be it unemployment or the informal sector) would still generally be substantially worse.

Suggestive evidence

I present some suggestive cross-regional correlations in Table 4, with corresponding figures in Appendix Figure A4. I estimate the separations elasticity for each of the 226 local municipalities in South Africa, and regress on the relevant census unemployment rate. Consistent with the discussion, there is a negative relationship between the firm labor supply elasticity and the unemployment rate (columns 1-2), with much more precision when using the employment to employment separations elasticity ε_{EEsep} (columns 3-4).[23] Although these correlations are robust to local area controls, they are subject to many biases – at the local area level, many variables are correlated – and so should just be considered suggestive evidence.[24]

A few other studies find a similar relationship when considering heterogeneity by unemployment. Hirsch, Jahn, and Schnabel (2018) find a decrease in the firm labor supply elasticity with increases in unemployment for West Germany using time series variation over cyclical unemployment ranging from 6-12%. Additionally, Cho (2018) estimates the firm labor supply elasticity in the US using demand shocks associated with the American Recovery and Reinvestment Act during the Great Recession, and disaggregates the estimates into a low elasticity of 1.8 for the highest quartile of unemployment and a higher elasticity of 6.5 for other quartiles. My results add to these findings by theoretically motivating the link between unemployment and monopsony power, and showing the correlation persists across a wide range of unemployment rates pertinent to developing countries with structural unemployment. Note these estimates all consider heterogeneity in a way that is vulnerable to the biases discussed above.

With the same caveats as above, the empirical cross-regional correlation within South Africa support implications of variation in firm labor supply elasticities too. Higher unemployment regions are correlated with lower average firm wage premia as expected (columns 5-6). If high unemployment relates to a lower labor supply elasticity, which in turn relates to higher firm wage dispersion, then one may expect that higher unemployment regions have higher firm wage dispersion (columns 7-8).[25] As above, these correlations do not disappear

[23]Employment to employment separations observed in the data may still include employment to non-employment separations since the data is observed at the annual level. The precision of the relationship with unemployment may be attenuated when using any separations, because such separations include workers who retire or have longer unemployment spells governed by different considerations.

[24]These correlations are subject to several additional biases. Firstly, the estimation of the separations elasticities uses the specification in column 1 of Table 3, as the least demanding specification for heterogeneous estimates (the overall estimated elasticity is similar for the first-differences strategy, and the movers specification requires too large a sample size to be estimated for each local municipality). Even if there is bias in this specification, as long as the bias is not systematically correlated with municipality characteristics, the correlations with unemployment are valid, as argued regarding heterogeneity analysis by Langella and Manning (2021). However, measurement error at least is likely to be correlated with municipality characteristics, when there are few firms in a region. Secondly, this uses a particular unemployment definition – broad unemployment to population ratio. There are several other candidate definitions, such as including the informal sector. I provide an alternative definition as the average duration out of observed formal employment in the data (see Appendix Figure A5). Thirdly, any spillovers due to cross-regional migration will bias these estimates, mitigated only to the extent that labor is not mobile (Chodorow-Reich 2020). Fourthly, any general equilibrium effects will not be captured as they are absorbed into the intercept.

[25]An additional reason why this should be taken as suggestive correlations rather than anything causal is that there are additional links between unemployment and firm wage dispersion. One example is that standard search

with controls, or when using unemployment duration rather than the unemployment rate.

In summary, firms potentially provide a partial link between two of the most outstanding features of the South African labor market: high wage inequality and high unemployment. I have argued that a large part of South Africa's wage inequality is due to dispersion in firm wage premia, and a simple framework shows that this is partly explained by higher dispersion in firm productivity and partly explained by more monopsonistic wage-setting power. I provide evidence on the latter by estimating a low firm labor supply elasticity, and in this subsection I have motivated theoretically and through suggestive correlations how this low firm labor supply elasticity may partly be linked to the high unemployment.

5 Discussion

In this section I discuss in further detail how the informal sector affects the analysis above, as well as the implications of my argument for firms and inequality in developing countries more generally.

5.1 Imperfect competition for informal employment

My main analysis has focused on formally employed labor, even though a characteristic feature of South Africa and developing countries generally is a substantial proportion of informally employed wage labor. More than 60% of the world's employed population works in the informal economy, located overwhelmingly in developing countries (ILOstat 2021). This subsection explores the competitive dynamics for the informally employed, using survey panel data for South Africa. I discuss further details in Appendix G. I define informally employed workers as workers on informal wage contracts (e.g. no written contract), such as workers employed in

models imply the reservation wage increases with firm wage dispersion (Hornstein, Krusell, and Violante 2011). The intuition is that dispersion increases the option value of waiting, since a lucky draw could result in a very good job. With higher reservation wages, the observed unemployment rate is higher for a given firm wage dispersion. Note this causal pathway is very different to the firm labor supply elasticity mechanism, potentially with feedback effects, but both predict a positive correlation between unemployment and firm wage dispersion. Another example is if frictions in the capital goods market hinder the expansion and entry of productive firms, which may limit the formal sector (thereby increasing unemployment), as well as increase firm wage premia through misallocation of labor to low productivity firms.

the informal sector, domestic workers, or taxi drivers.[26]

As mentioned in section 3, excluding the informally employed from the firm wage premia decomposition will tend to underestimate the raw variance due to firm wage premia. Although survey data cannot identify firm wage premia as well as in the matched employer-employee data, I can illustrate this with some rough calculations. Informally employed workers account for 20% of total employment, and earn about 28% less than formal sector workers. Assuming these are two combined normal distributions, this would increase the raw variance in firm wage premia from 0.37 to 0.44.[27] That is, ignoring the informally employed means I may underestimate firm wage dispersion by a fifth, which further widens the gap compared to higher income countries.

The framework used to explain the firm wage dispersion relies on some competition in the labor market. How well does this apply to the informally employed? Firstly, wage differences are correlated with transition patterns as in figure 1 above. Nearly 1 in 5 workers transition from informal to formal employment every quarter, compared to only 1 in 25 in the reverse direction (see Appendix Tables G1 and G2). Moreover, workers who transition from informal to the formal employment report substantially larger wage gains, while workers transitioning in the reverse direction report wage losses of a similar magnitude. These patterns are consistent with low productivity informal employment offering low firm wage premia, which fall towards the bottom of a job ladder comprised of all jobs (informal or formal). Secondly, I estimate separation elasticities, and find that the relative magnitudes show similar labor supply elasticities for formal and informal workers, suggesting comparable degrees of monopsony (Appendix Table G3).[28] Thirdly, I find a rent-sharing elasticity using informal enterprise survey data of 0.26,

[26]There are about half as many informal sector owners of enterprises as there are informally employed, and I exclude this group from my analysis as they may be subject to different dynamics. South Africa has a high proportion classified as unemployed rather than working informally, relative to other countries. This may related to the relatively wide coverage of social assistance programs – see Bassier et al. (2021).

[27]According to quarterly panel data from household labor force surveys (Statistics South Africa 2010-2015), informal sector workers earn about 0.28 log points less per hour than formal sector workers, adjusting for observable worker characteristics (monthly rather than hourly earnings will further exacerbate differences). Informal enterprise surveys suggest a standard deviation of 0.64; insofar as the informally employed are at formal sector firms, the raw variance will be between 0.38 and 0.44. The combined variance is a weighted average of the sum of the standard deviations and the differences in means.

[28]Survey panel data has the advantage of tracking informal sector transitions, but the disadvantage of measurement error resulting in less credible estimates. I assume the *relative* magnitudes for the separations elasticities for workers in formal and informal jobs are still interpretable, as argued regarding heterogeneity by Langella and Manning (2021).

which is also suggestive of wage-setting power. Though these estimates are likely biased by inadequate controls for worker quality, they suggest that the competitive labor market dynamics for the informally employed may not be too different to the formally employed investigated in my main analysis.

Two recent papers analyze the interaction between formal and informal employment with search frictions in the context of Brazil (Meghir, Narita, and Robin 2015; Ulyssea 2018). These papers also argue that informal and formal employment form a common labor market, and face similar competitive dynamics. The differences tend to be that the informally employed are in less productive firms. In summary, while my primary data are not suited towards the important analysis of informal employment, my analysis using survey data suggests that informal workers may face similar competitive dynamics which contribute to greater inequality.

5.2 Firms, unemployment and development

The features and relationships identified in this paper are likely to be relevant to the development process more generally. As documented above, the two sources of firm wage dispersion that I focus on for South Africa – a higher dispersion in firm productivity and a low firm labor supply elasticity – are characteristics shared by other developing countries. For example, both Brazil and Mexico have a high dispersion in firm wage premia and a low firm labor supply elasticity (Alvarez et al. 2018; Dal Bó, Finan, and Rossi 2013); and Hsieh and Klenow (2009) document a much larger dispersion in productivity for China and India relative to the US, implying large effects on wage inequality of any pass-through onto wages.

The possibility of firm-level monopsonistic dynamics contrasts with much of the analysis in classical development models which typically take place at the sectoral level, where an industrial sector draws on surplus labor at a constant subsistence wage (Basu 2003). In standard monopsony models, these dynamics are nested in the case where there is no on-the-job search. More generally though, when workers search while employed at heterogeneous firms, then higher productivity firms need to post higher wages in order to attract more workers (Burdett and Mortensen 1998). The idea that high productivity firms in labor *surplus* countries need to increase wages to attract workers may be counter-intuitive, but consider that costs of migration, poor transport infrastructure and a limited supply of skills may lead to a larger role for frictions. The related concept of segmented labor markets is familiar to the development literature (Fields 2009). Such high productivity firms are also only unable to attract more workers at their current, monopsonistically *marked down* wages.

If optimal firm wage-setting derived from monopsony power is relevant to developing countries, then in the spirit of Kuznets and Lewis, this suggests a particular transition path (see details in Appendix D.2). Classical models of development predict high dispersion in firm productivity as some sectors lead the industrialization process before equalizing across the rest of the economy.[29] Initially, at the onset of industrialization, assume a small proportion of firms have high productivity. Such higher productivity firms optimally pay higher wages, set along their upwards sloping firm labor supply curve. These high-productivity firms will still only attract a minority of workers, since they initially constitute such a small proportion of firms, meaning wage inequality is initially low. As the higher productivity technologies spread to more firms, total employment in higher productivity firms increases, and wage inequality also increases (then eventually declines). Appendix Figure D1 illustrates this transition path.

This mechanism shows how higher wage inequality may fit into the development process, especially for partially industrialized economies such as South Africa and Brazil, driven by optimal firm wage-setting along with frictions in the labor and technology markets. The firm wage premium here is derived through the wage pass-through from higher productivity firms, which follows from a finite labor supply elasticity; this is unlike the wage premium in classical models, where the premium is usually assumed. This contribution of firms to inequality is not inevitable: collective bargaining or regulation via minimum wages are countervailing mechanisms. Alvarez et al. (2018) show that a reduction in the variance of firm wage premia accounts for 40% of the dramatic decline in Brazil's inequality between 1996 and 2012, a period over which the real minimum wage increased substantially.

[29]Lewis (1954) narrates, "Capital and new ideas are [...] highly concentrated at a number of points, from which they spread outwards." This is not to say classical models correctly characterize the development process; see e.g. Kesar and Bhattacharya (2020) for a critique.

6 Concluding thoughts

This paper investigates the role of firms in inequality in the context of high unemployment, using matched employer-employee data from South Africa. I find that firms play a larger role in determining wages than in other, high income countries. I estimate a high firm wage variance, and argue this is related to the high firm productivity dispersion and low firm labor supply elasticity. One implication of a low firm labor supply elasticity is a high pass-through rate: to illustrate its importance, plausible calibrations imply firm wage variation is a *third* as large for a given firm productivity dispersion.[30] I separately estimate a high pass-through rate (though the gap is not as large). I suggest that the low firm labor supply elasticity may partly be related to the high unemployment rate, as motivated by theory and cross-regional correlations.

This paper poses several links for future research. Firstly, the firm labor supply elasticity may affect firm wage dispersion through many channels besides the pass-through rate. I briefly discuss two in this paper, heterogeneity in the elasticity itself and interactions with other constraints. One could evaluate the relative contribution of each channel (including productivity dispersion) to the gap in firm wage dispersion. Secondly, the evidence in this paper on unemployment is only suggestive, and a persuasive case requires identified estimates. Thirdly, this paper has not focused on the sorting of high wage workers to high wage firms in the framework or discussion of sources, partly because the percentage variation explained by sorting did not stand out nearly as much against other country estimates compared to firm wage premia. However, the allocation of workers and any match effects are surely important for developing country firm dynamics.

The role of firm wage-setting power is conspicuously underemphasized in the academic literature and policy in South Africa, which typically focus on the supply side to address the country's high levels of inequality and unemployment. My wage premia variance decompositions imply that firms account for a fifth of overall income inequality in South Africa.[31] The

[30] I comparing my highest estimate of the firm labor supply elasticity ($\bar{\varepsilon}_j = 1.6$) to the lowest in the best-estimate range of the meta-study of Sokolova and Sorensen (2021) ($\bar{\varepsilon}_j = 6.4$), and use the framework in Section 4.1.

[31] Leibbrandt, Finn, and Woolard (2012) estimate that income from the labor market accounts for 85% of the Gini coefficient in household income, 62% of which is due to earnings inequality (rather than inequality between the employed and unemployed). Assuming the percentage explained from the Gini is close to the percentage explained of total wage variance, firms roughly explain 36% (28% variance plus 8% sorting) of 62% of 85%, or

high degree of monopsony power estimated for South Africa also implies lower wages, an important aspect out of the scope of this paper. Anti-monopsony policy could substantially decrease this firm-level inequality, while also increasing employment and wages (Naidu, Posner, and Weyl 2018). Such policy includes addressing labor market concentration, reducing barriers to employment mobility as in the search-based dynamic monopsony model, and institutionalizing counterbalances to monopsonistic wage setting such as collective bargaining.

This study of South Africa poses links from firm productivity dispersion, firm labor supply constraints and high unemployment to high inequality, channels that may generalize to developing country contexts. These channels rely on imperfect competition in the labor market. In a large scale experimental evaluation of the spillover effects from India's public employment program NREGS, Muralidharan, Niehaus, and Sukhtankar (2017) note that "finding positive effects on employment forced us to question the default assumption of competitive labor markets, and look for credible ways to test this assumption." Monopsony power based on search frictions are consistent with recent experimental evidence in South Africa (Abel, Burger, and Piraino 2020), and the high cost of searching for work (Mlatsheni and Ranchhod 2017). This role of monopsony power may turn out to be a pervasive and important feature in the development process, and needs to be further modeled and tested in developing countries.

19% of total household income inequality.

7 Tables and figures

Table 1: **Summary statistics of tax panel data**

	Workers	Real earnings (ZAR)			Separations
	(freq.)	(p50)	(p90)	(mean)	(mean)
2011	8,353,791	87,426	357,735	169,446	36.5%
2012	8,681,995	87,805	365,590	174,496	36.8%
2013	8,900,366	86,377	366,006	173,343	36.3%
2014	8,981,113	86,158	370,980	173,164	36.1%
2015	9,150,558	87,527	381,560	174,745	37.4%
2016	8,999,547	88,632	385,823	178,232	

Notes. Wages are annualized and adjusted for inflation (base year 2016). Earnings include wage benefits such as overtime and annual bonus. A separation occurs when a worker is no longer recorded at the same firm in the following year. Observations are restricted to workers at firms with more than 20 workers. Source: Own calculations, South African tax records, 2011-2016.

Table 2: **Decomposition of firm and worker effects**

	(1)	(2)	(3)	(4)	(5)
Observations (m)	42	42	13	12	25
Var(LnWage)	1.32	1.32	1.07	1.49	1.11
% Var(Firm FE)	**29%**	**28%**	**29%**	**24%**	**33%**
% Var(Worker FE)	44%	37%	47%	28%	43%
% 2xCov(Firm,Worker)	8%	8%	2%	9%	3%
% Other terms	7%	7%	10%	8%	13%
% Residual	13%	19%	11%	30%	9%
Method	AKM	KSS	KSS	KSS	KSS
Sample	All	All	Closings	Gaps	Full time

Notes. This is a variance decomposition following Equation 1. The first column gives the baseline AKM decomposition (Abowd, Kramarz, and Margolis 1999), while the other columns correct for limited mobility bias using the KSS method (Kline, Saggio, and Sølvsten 2020). Columns 1 and 2 pertain to all workers. Column 3 restricts to the subsample of firm closings, i.e. stayers (workers who stayed at the same firm throughout), or workers who separated from a firm which was not observed for at least the next two years. Column 4 restricts to stayers or workers who were not observed for at least a gap of one year. Column 5 restricts to workers who were recorded as working full-time. Other terms refer to squared and cubic terms in age (centered at 40), as well as year fixed effects. All samples are limited to the largest connected set of firms with more than 20 employees. Source: Own calculations, South African tax records, 2011-2016.

Table 3: **Firm labor supply elasticities**

	(1)	(2)	(3)	(4)
Separations	-0.308	-0.261	-0.319	-0.794
	(0.014)	(0.005)	(0.127)	(0.055)
Firm LSE	0.858	0.773	0.742	1.59
	(0.032)	(0.015)	(0.256)	(0.110)
Fstat			14.961	
Obs (m)	36.2	36.2	0.1	0.48
Specification				
OLS	Y	Y		
First Difference			Y	
Movers				Y
Controls				
Worker type	Y	Y		Y
Indus X Geo FE		Y		

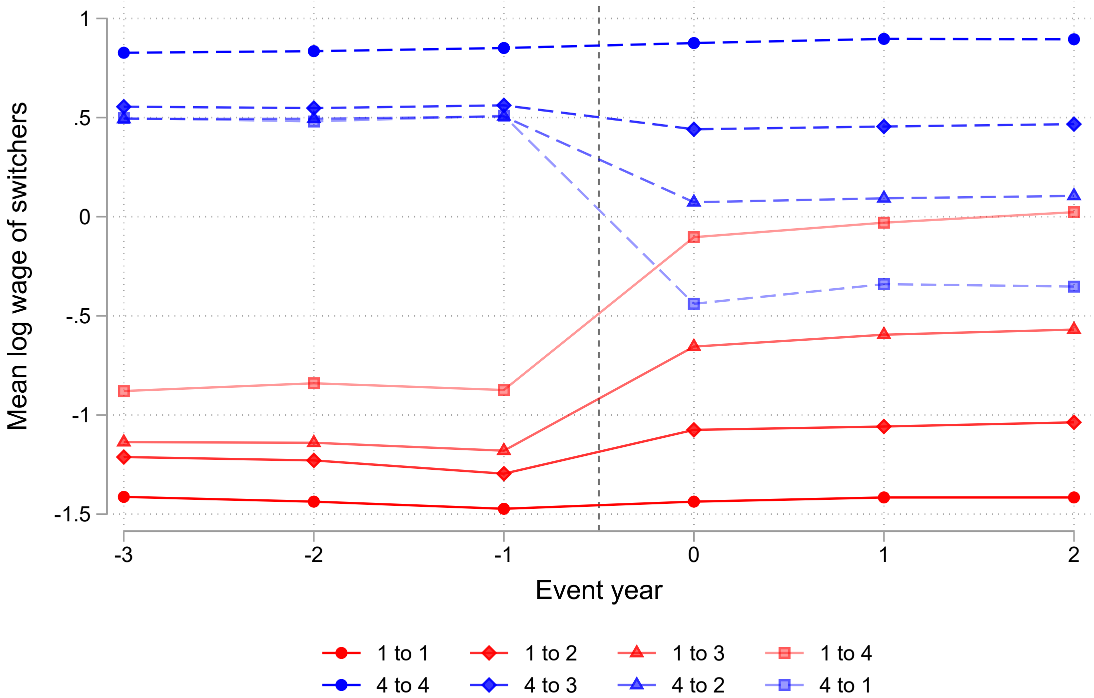
Notes. The Separations row presents the separations elasticity ε_{sep}. The firm labor supply elasticity (Firm LSE) row combines the estimates from separate regressions, shown in Appendix Table A2, to produce ε_{LS} using Equation 5. See above for the explanations of the OLS (worker level), First Difference (weighted firm level) and Movers (worker level) specifications. Further specifications for the Movers design in Appendix E. The worker type control adds the AKM worker fixed effect as a continuous variable control. The industry by geography control includes 221 by 20 fixed effects respectively. Workers are limited to connected firms with more than 20 employees. Standard errors in parentheses. Source: Own calculations, South African tax records, 2011-2016.

Table 4: **Unemployment and regional indicators of labor market power**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unemployment	-0.956	-0.940	-1.313**	-2.387***	-0.441**	-0.248**	0.283**	0.243*
	(0.644)	(0.577)	(0.562)	(0.670)	(0.189)	(0.112)	(0.127)	(0.126)
Obs	164	164	164	164	211	210	164	164
Controls		Y		Y		Y		Y
Outcome	Sep	Sep	E-E Sep	E-E Sep	Firm FE	Firm FE	var(ϕ_j)	var(ϕ_j)

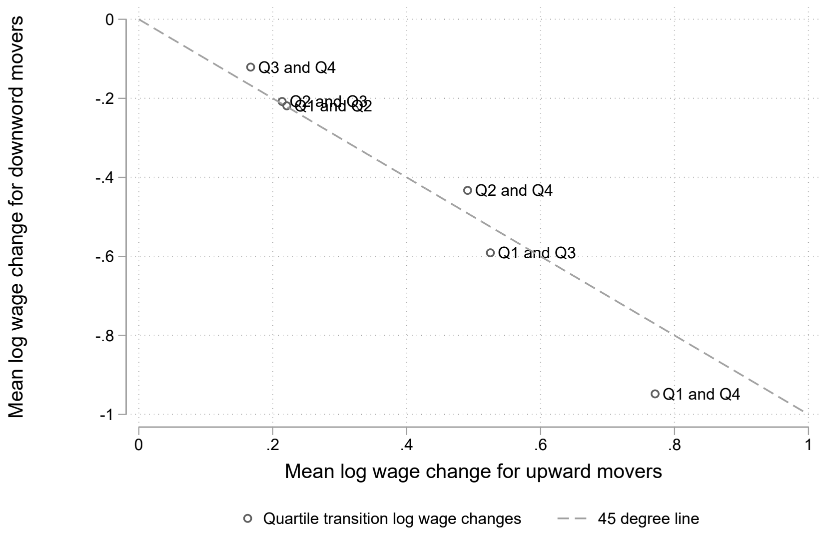
Notes. Unemployment is measured as the municipal unemployment to population ratio from the Census 2011. The separations elasticities are estimated by local municipality, by regressing firm separations on firm wages controlling for AKM worker effects, for all separations (columns 1-2) and employment to employmenr separations (columns 3-4). Regions with fewer than 30 firms are omitted. Firm FE are the estimated KSS Firm wage premia from Section 3, and $var(\phi)$ are the regional variance in these firm wage premia. Controls refer to regional average firm size, value added per worker, population density, and industry composition. Source: Own calculations, South African tax records, 2011-2016.

Figure 1: **Wage profiles of movers by firm co-worker quartiles**

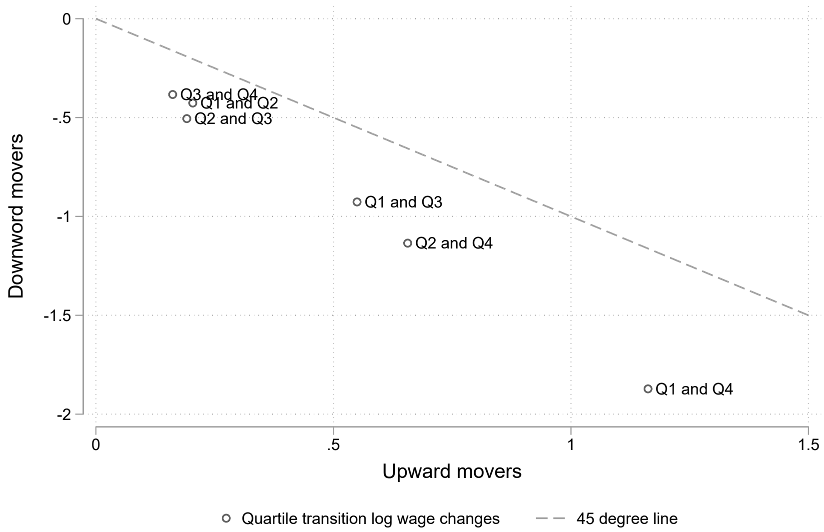


Notes: The legend shows worker moves from origin quartile to destination quartile. Quartiles are calculated as the mean co-worker quartile in the firm, i.e. leaving own-wage out of mean firm wage. In Panel A, only origin quartiles 1 and 4 are plotted, and only employment-to-employment movers are included, such that each worker stayed at the same firm from 2011 to 2013, then moved to a new firm and stayed there from 2014 to 2016. Event year 0 (or tax year 2014) represents wages at the new firm. Wages of the full sample (including stayers) are residualized on year effects before plotting.

Figure 2: **Symmetry of wage changes by firm co-worker quartiles**



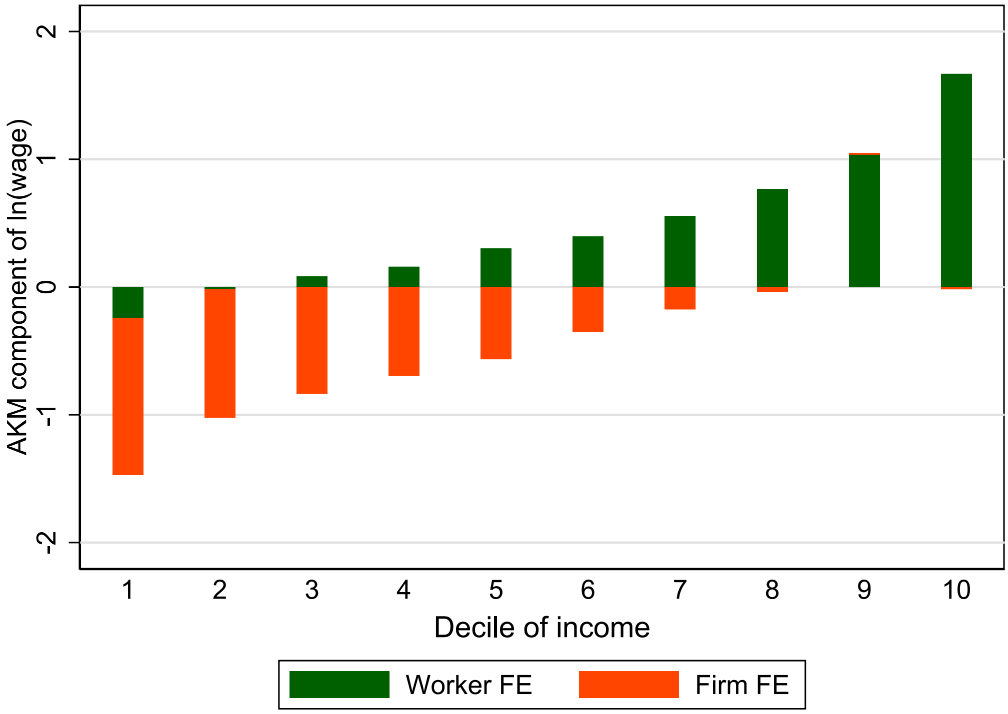
(a) **Movers**



(b) **Employment gap**

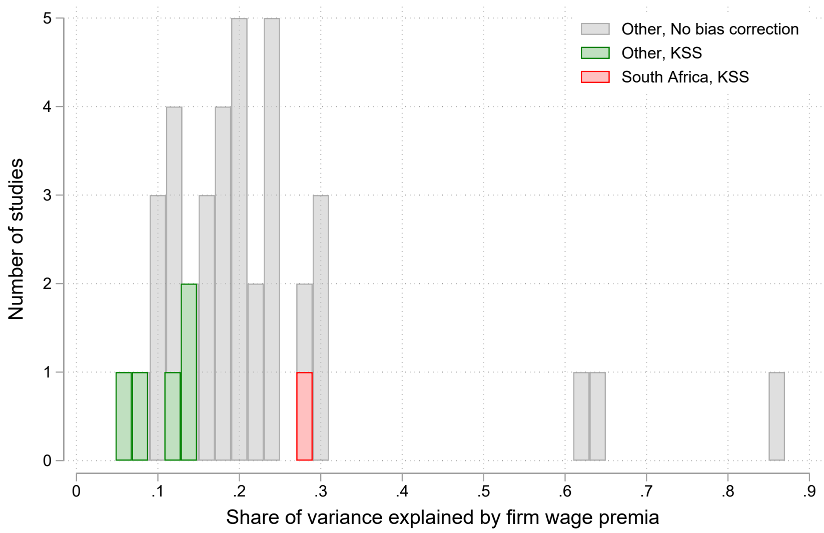
Notes: The figure shows the quartile to quartile log wage changes corresponding to the quartile transition event study in Figure 1. Upward mover indicates that the worker moved from a lower quartile to a higher quartile; downward mover indicates the worker moved to a higher quartile. For example, the point labeled "Q1 and Q4" shows the average log wage change for movers from quartile 1 to quartile 4 on the horizontal axis, and for movers from quartile 4 to quartile 1 on the vertical axis. The dotted line shows the 45 degree (negative) slope from the origin: symmetric downward and upward log wage changes would lie on this line. Panel A shows all quartile wage changes across the firm switch for movers, and Panel B shows the same quartile wage changes for workers with a one year gap from formal sector employment.

Figure 3: **Decomposition of worker and firm fixed effects, by decile of income**

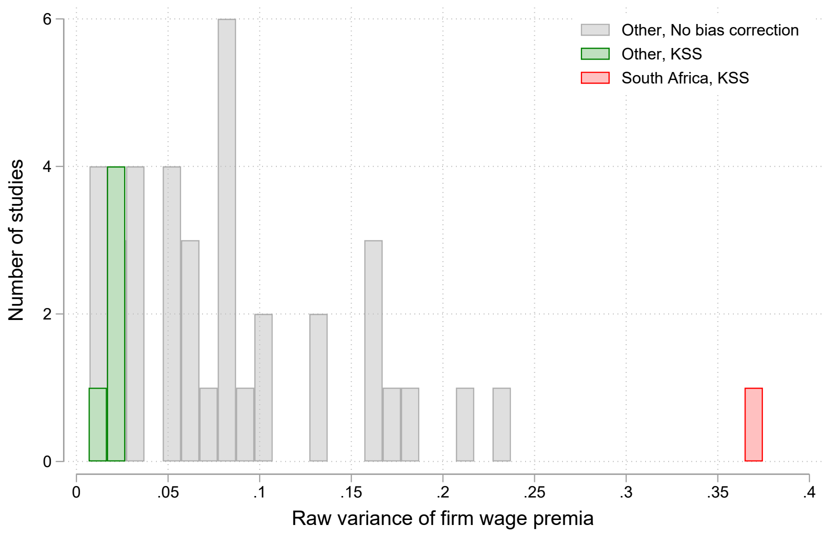


Notes. Worker and firm effects are estimated from the full sample AKM regression using the KSS method (column 2 in table 2). Decile of unconditional income is calculated by year, and for each decile the average worker and firm effects are plotted. Source: Own calculations, South African tax records, 2011-2016.

Figure 4: **Variance of firm wage premia, comparison to other countries**



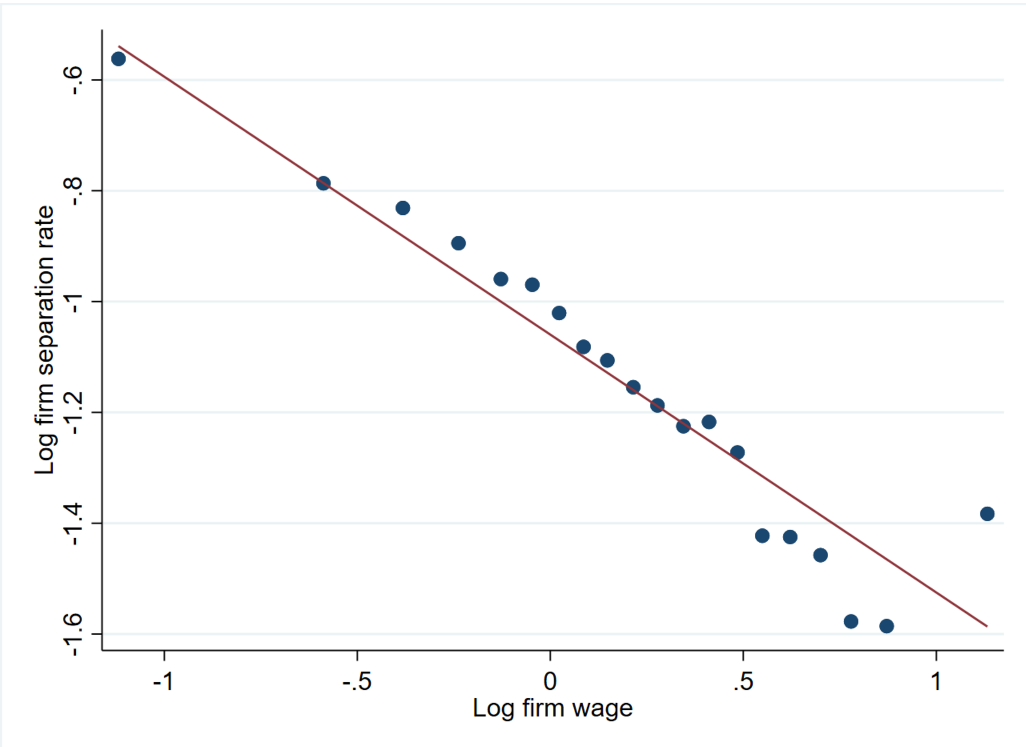
(a) **Share of variance**



(b) **Raw variance**

Notes. Estimates are compiled from Bonhomme et al. (2022), adding the estimates from this paper. KSS indicates the estimation method in Kline, Saggio, and Sølvsten (2020) is followed. Share of variance is the share of total wage variance explained, and raw variance is the direct variance of that component.

Figure 5: **Firm separation rate and wages**



Notes. Firm wage refers to the average annualized wages of workers by firm, and are centered around 0 for plotting. Firm separation rate is the average proportion of workers who separate by firm in a year. The plot uses a control function to control for average worker quality.

A Appendix: Additional Tables and Figures

Table A1: **Measures of productivity dispersion in South Africa**

	TFP-IQR	TFP-SD	TFP-p90p10	LP-IQR	LP-SD	LP-p90p10
2-d (all)	.78	.77	1.65	1.15	1.07	2.39
2-d (big)	.83	.78	1.72	1.23	1.1	2.51
3-d (all)	.75	.73	1.55	1.1	1.03	2.29
3-d (big)	.76	.72	1.54	1.1	1.01	2.26
4-d (all)	.75	.72	1.54	1.09	1.02	2.26
4-d (big)	.75	.72	1.52	1.11	1.01	2.2

Notes. The table shows that within each column measure estimates are similar. TFP refers to total factor productivity, i.e. value added residualized by a regression on industry specific terms of the mean, capital, labor, and material costs. LP refers to labor productivity, i.e. value added per worker residualized by a regression on industry specific constant. Big indicates that only firms with more than 20 workers are considered. Measures are averaged across all sectors (not just manufacturing).

Table A2: **Alternative specifications for labor supply elasticity**

	(1)	(2)	(3)	(4)
Separations	-0.308	-0.261	-0.319	-0.794
	(0.014)	(0.005)	(0.127)	(0.055)
E-E separations	-0.509	-0.424	-0.34	-1.073
	(0.018)	(0.010)	(0.171)	(0.074)
E-N separations	-0.294	-0.292	-0.221	
	(0.022)	(0.008)	(0.086)	
E-E recruits	0.041	0.002	-0.129	
	(0.013)	(0.003)	(0.051)	
Perc E-E recruits	0.451	0.451	0.442	
Firm LSE	0.858	0.773	0.742	1.59
	(0.032)	(0.015)	(0.256)	(0.110)
Fstat			14.961	
Obs (m)	36.2	36.2	0.1	0.48
OLS	Y	Y		
First Difference			Y	
Movers				Y
Controls				
Worker type	Y	Y		Y
Indus X Geo FE		Y		

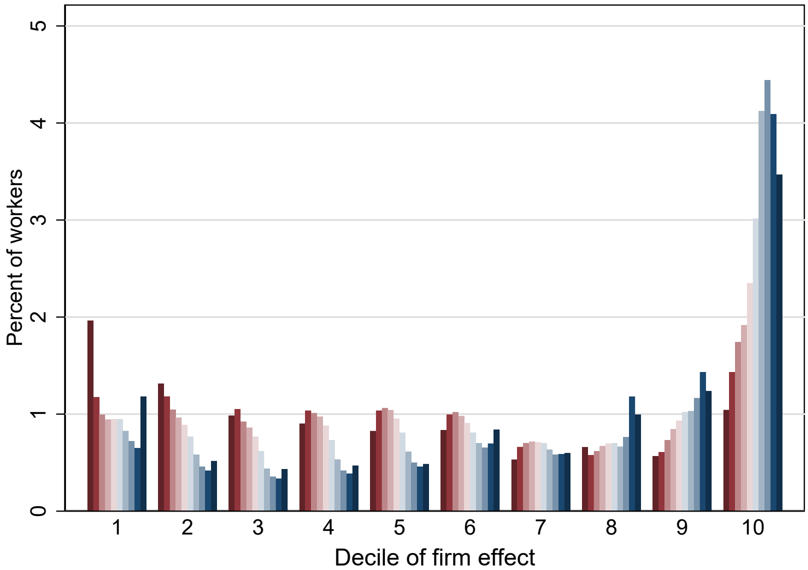
Notes. The top four rows represent separate regressions on all separations, employment-to-employment separations, employment to non-employment separations, and employment to employment recruits respectively. The Firm LSE row combines estimates from these separate regressions. The worker type control adds the AKM worker fixed effect as a continuous variable control regressor. The industry by geography control includes 221 by 20 fixed effects respectively. The First Difference specification is run at the firm-level (weighted by number of workers), and compares the change in separations within a firm to the change in average wages, as instrumented by change in log value added per worker. Workers are limited to connected firms with more than 20 employees. Standard errors are given in parentheses. Source: Own calculations, South African tax records, 2011-2016.

Table A3: **Unions and rent-sharing elasticity**

	(1)	(2)	(3)	(4)	(5)	(6)
Union	0.689	0.414	0.148	0.454	0.269	-0.007
	(0.093)	(0.098)	(0.201)	(0.069)	(0.039)	(0.085)
log(VA pe)				0.113	0.112	0.101
				(0.006)	(0.006)	(0.006)
Union X log(VA pe)				0.186	0.189	0.067
				(0.030)	(0.031)	(0.027)
Obs (mill.)	23	22.1	22.1	14.2	13.9	13.9
R^2	.12	.16	.21	.29	.33	.39
Within R^2	0.12	0.08	0.05	0.29	0.25	0.17
Worker control	Y	Y	Y	Y	Y	Y
Industry FE		Y	Y		Y	Y
Location FE			Y			Y

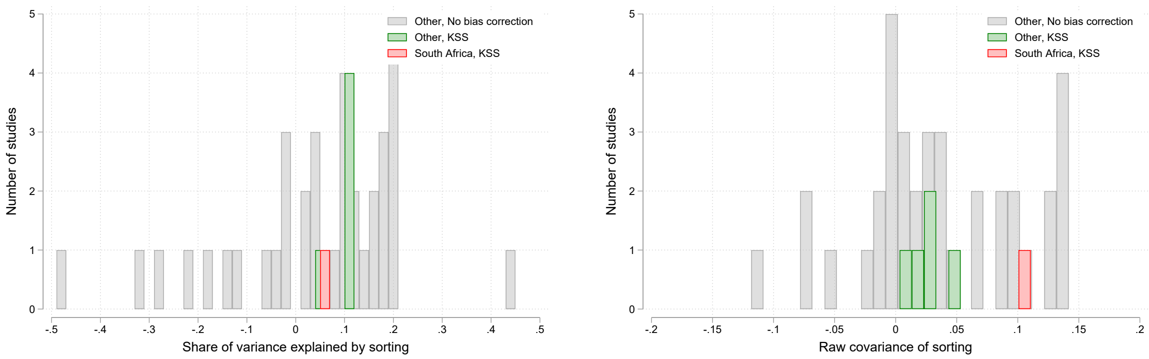
Notes. The outcome is the estimated AKM firm wage premia. VApe refers to value added per employee as a proxy for rent. Union density is averaged from survey data and merged into the individual data at the location by industry by year cell. Variable values are centred around 0. Union density is instrumented by its lag to reduce measurement error. The third row indicates the interaction between union density and log value added per employee. Industry contains 10 industry categories, and location contains 221 categories. All specifications are run at the individual level, include a continuous variable control for the estimated AKM worker wage premia, and are clustered at the municipality by industry cell. Standard errors are given in parentheses. Workers are limited to those at connected firms with more than 20 employees. Source: Own calculations, South African tax records, 2011-2016, and Quarterly Labor Force Survey, 2010-2015.

Figure A1: **Distribution of worker and firm fixed effects**



Notes. Worker and firm effects are estimated using the AKM regression. Deciles of worker effects are calculated with one observation per worker, and deciles of firm effects are calculated with one observation per firm. One observation per worker is plotted, where deciles of worker effects are plotted in increasing order by decile of firm effect (dark red is the lowest worker effect, dark blue is the highest). Workers are limited to connected firms with more than 20 employees.

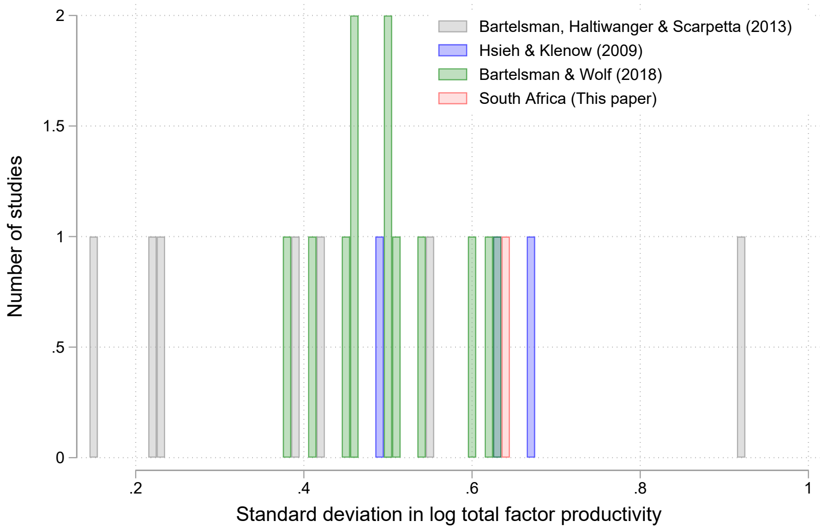
Figure A2: **Variance due to sorting, comparison to other countries**



(a) **Share of variance** (b) **Raw covariance**

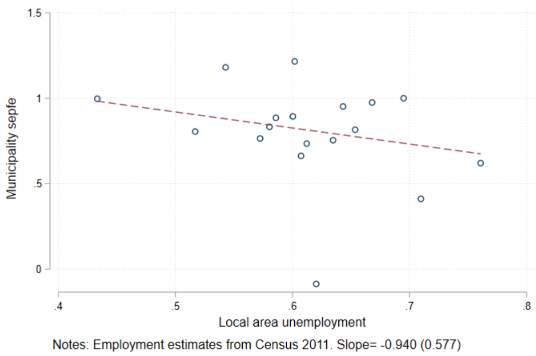
Notes. Sorting referes to the covariance between firm and worker wage premia. Estimates are compiled from Bonhomme et al. (2022), adding the estimates from this paper. KSS indicates the estimation method in Kline, Saggio, and Sølvsten (2020) is followed. Share of variance is the share of total wage variance explained, and raw variance is the direct variance of that component.

Figure A3: **Standard deviation of firm productivity, comparison to other countries**

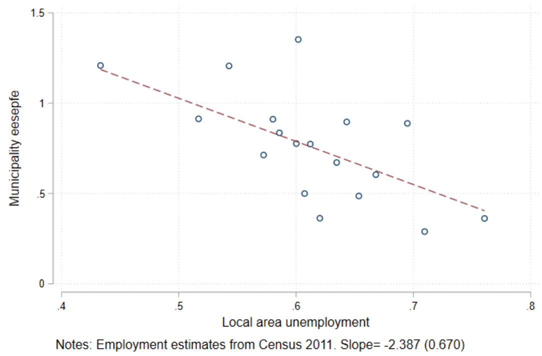


Notes. Estimates refer to the manufacturing sector across 21 countries and 23 studies. Productivity is measured across all sources as log total factor productivity (TFP) within each industry, i.e. log value added residualized by a regression on 4-digit industry specific log terms of the mean, assets, firm size, and material costs. The legend notes the sources of the estimates, referring to Bartelsman, Haltiwanger, and Scarpetta (2013), Bartelsman and Wolf (2017), and Hsieh and Klenow (2009), as well as this paper.

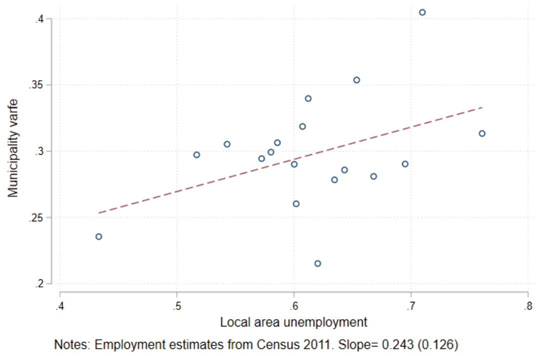
Figure A4: **Unemployment and regional indicators of labor market power**



(a) **Separations elasticity**



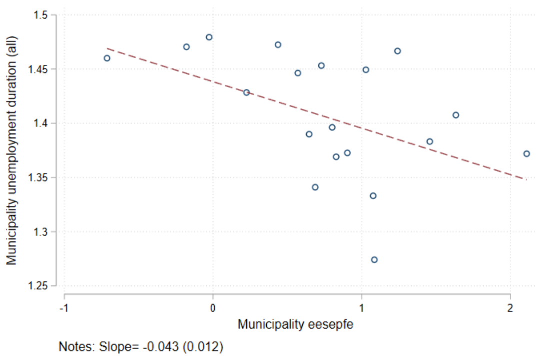
(b) **E-E separations elasticity**



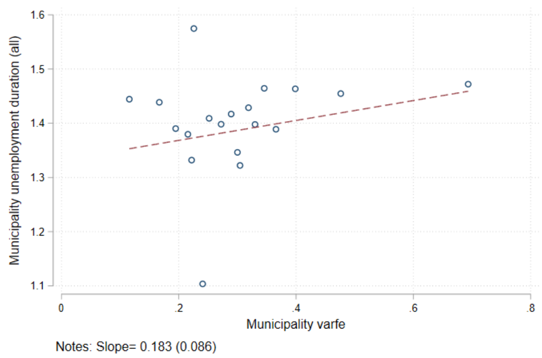
(c) **Variance in firm wage premia**

Notes. Municipal unemployment rate from Census 2011. EPOP unemployment denotes unemployment to population ratio. The separations elasticities are estimated by local municipality, by regressing firm separations on firm wages controlling for AKM worker effects. Panel A uses all separations, and panel B only uses Employment to Employment separations. Panel C calculates regional variance in the estimated KSS Firm wage premia. Controls include local area average firm size, value added per worker, population density, and industry composition.

Figure A5: **Firm premia and unemployment duration**



(a) **E-E sep elasticity and duration**



(b) **Variance of wage premia and duration**

Notes. Unemployment duration is measured as the years between being observed in the full sample of formal sector firms in the tax data. Source: Own calculations, South African tax records, 2011-2016.

B Appendix: Data sample and construction

Data access

The datasets used for this paper have restricted access, due to their confidential nature as tax records of workers and firms. The data are managed jointly by the South African National Treasury and UNU-WIDER under the project "Southern Africa – Towards Inclusive Economic Development (SA-TIED)". They may be accessed by responding to one of the public call for proposals, which involves writing a motivation for a project and being accepted by the administrators of the relevant work stream. Accepted researchers must be physically present at the data centre, which is in Pretoria, South Africa, and any output is screened for confidential information before being sent to researchers from the data centre.

My project was accepted under the inequality workstream in 2018, and an earlier version was published by agreement as a working paper under the project in 2019. Return access is allowed conditional on a strong motivation towards publication, such as revisions requested by a journal.

Data construction

I combine two sources of data from the South African Revenue Service to form a matched employer-employee panel. The main source records individual job certificates submitted by firms on behalf of any employee earning over R2,000 a year (a low threshold of under \$150)[32]. The second source of data is a firm-level panel based on corporate income tax data[33], which provides me with the firm-level value added used for estimating productivity dispersion and rent-sharing elasticities.

In constructing my data sample, I begin with all job certificates which comprise of about 15 million per year. I restrict to workers who are between 20 and 60 years old to reduce the like-

[32] Kerr (2018) uses this dataset in studying job churn over 2011-2014, and Ebrahim, Leibbrandt, and Ranchhod (2017) assess the impact of the Earnings Tax Incentive, a youth wage subsidy recently implemented in South Africa.

[33] For example, this firm-level panel is used by Kreuser and Newman (2018) in finding total factor productivity trends in manufacturing firms, and by Fedderke, Obikili, and Viegi (2018) in calculating concentration in the manufacturing product market.

lihood that wages consist of part time work or pension income, which reduces the certificates to about 14 million per year. I match these records to firm-level data using a correspondence table provided with the data; for reasons not completely clear to the data administrators, this matching is imperfect and fails to match about 1 million observations. Next, I convert job-level records to the worker-level by selecting only the job for which wage income is highest[34]. I restrict to firms that have more than 20 workers, following Song et al. (2018). The empirical strategy relies on estimating firm fixed effects, which may not be estimated well in small firms with idiosyncratic behaviour; limited mobility bias is also worse in the case of small firms. While excluding the majority of firms, this restriction maintains over 70% of workers and over 85% of total reported revenue. I provide some robustness analysis without this firm size restriction.

I observe unique identifiers for workers as well as establishments. However, balance sheet information is only reported at the firm level, i.e. for each firm-based collection of establishments. In the analysis below, “firm” wage premia would more accurately be named “establishment” wage premia.” Thus in principle the “firm” effects are run at the establishment level, which should be differently reported within each region. In practice, this is not exactly correct as the data administrators note some firms submit worker claims at the head office rather than individual establishments.

I adjust all ZAR-denominated variables by the national consumer price index inflation tables provided by the national statistics agency, Statistics South Africa. I construct earnings by adding wage income and wage benefits, such as overtime, medical aid and annual bonus, and annualize earnings by multiplying reported earnings by the inverse of the reported fraction of the year employed.

The main firm-level variable I use is value added per worker, which I construct as sales minus total non-labor costs, and serves as a proxy for rent as in Lamadon, Mogstad, and Setzler (2022) and Card, Cardoso, and Kline (2016). As secondary measures of rent, I construct profits as value added minus labor costs. 80% of firms have non-missing value added. The incompleteness of this variable may introduce bias, but the direction is ambiguous. Loss-making

[34] This decision rule is also used by Bonhomme et al. (2022), Sorkin (2018), and Webber (2016).

firms may be drawn disproportionately, since losses are deductible from taxes on the following year's profits. On the other hand, firms which fail have no incentive to report losses or sales. It is reassuring that the firms who do report cover disproportionately more workers (i.e. bigger firms report more often).

Data descriptives

How does this compare to survey data? The national statistics agency, conducts several publicly available surveys. I compare to the Income and Expenditure Survey (IES) of 2010/11, which is aimed at providing accurate income data and has a sample of over 90 thousand people, as well as to the Quarterly labor Force Survey which has a smaller sample size but is conducted quarterly[35]. The IES records 12 million employed, and the QLFS shows 13-14 million employed per year over the sample period. This implies excellent coverage in the tax data which records 10-11 million workers employed (before restrictions), yet excludes informally employed workers who are counted survey data. The IES records median and 90th percentile wages of about 80% of those reported in table 1, and the QLFS similarly records p50 and p90 wages of 70-80% of those reported in table 1. The difference is likely due to a combination of measurement error and the distribution being shifted up with the exclusion of informal workers and small firms. Overall it is reassuring that the employment and wages correspond roughly to survey data.

[35]I use version 3.2 of the Post-Apartheid labor Market Series, which standardizes the QLFS (Kerr and Wittenberg 2017). For the remainder of the paper where I compare to survey data, I use this dataset.

Table B1: **Summary statistics on data cleaning**

Panel A	Jobs (freq)	Sample (freq.)	Age (mean)	E-E separations (mean)
2011	10,100,000	8,353,791	36.98	0.171
2012	10,400,000	8,681,995	36.93	0.175
2013	10,600,000	8,900,366	36.93	0.167
2014	10,600,000	8,981,113	36.95	0.174
2015	10,800,000	9,150,558	37.11	0.171
2016	10,700,000	8,999,547	37.20	

Panel B	All firms		Panel Firms			
	Firms (freq.)	Sales (ZAR, total)	Firms (freq)	Sales (% all firms)	Value Added (Non-missing, %)	Firm size (Median)
2011	223,054	1.11E+13	42,038	86.3%	77.7%	43
2012	226,855	1.32E+13	42,980	87.1%	79.1%	43
2013	229,068	1.35E+13	44,527	85.2%	79.2%	43
2014	231,982	1.46E+13	45,265	84.9%	79.3%	44
2015	236,243	1.46E+13	46,010	85.6%	79.2%	44
2016	239,024	1.48E+13	46,563	86.5%	78.0%	44

Notes. Panel A: Jobs refer to distinct worker-firm-year matches restricted to ages 20-60. Column 2 selects the highest wage of worker-firm-year matches per worker, to convert into a worker panel. An E-E separation occurs when a worker is registered at one firm and then registered at a different firm in the following year. Panel B: Firm-level summary statistics. The main restriction for in-sample firms are to firms with more than 20 workers. Sales and value added totals are given as a percentage of all firms. Source: Own calculations, South African tax records, 2011-2016.

It is worth understanding what role informal workers play compared to the sample of formal workers captured in the data. Using the Quartlerly Labor Force Survey from 2011 to 2016, I define a worker as in the formal sector if the employment contract is written or deductions are made for pension or medical aid. A worker is also in the formal sector if they are self-employed with a business that is registered for tax. A worker is informally employed if they do not satisfy any of these definitions.

To get a sense of transitions between the informal and formal sector, I link workers to their future response by exploiting the 25% out-rotation quarterly panel design (Table B2). 91% of formal workers remain in formal employment by the following quarter, whereas only 4% leave to the informal sector. This suggests transitions from formal to informal employment is not a major concern.

Table B2: **Dual sector transitions**

	NEA	Unemployed	Informal	Formal	Total
NEA	83.9	12.7	2.0	1.4	100.0
Unemployed	15.4	73.8	6.0	4.8	100.0
Informal	4.3	9.6	72.2	13.9	100.0
Formal	1.6	3.0	4.3	91.1	100.0
Total	30.3	23.1	12.5	34.1	100.0

Note: NEA indicated not economically active. Unemployed follows the expanded definition of unemployment, i.e. it includes those who would like a job but have not seeked employment in the last week. Rows represent employment status in the initial period, and columns represent status for the same individual in the following period. Each row adds up to 100 percent. The sample includes all adults aged 18-64, following the national official definition of the working age population, and corresponds to weighted observations from the QLFS 2011-2016.

Finally, while the summary statistics tables on the data give a sense of the distribution of wages (e.g. table 1 in the main text), table B3 summarizes wage growth. The actual movement and wage growth of workers by firm movement hint at the high dispersion in firm wage premia. Workers who switch firms have substantially higher wage growth on average, especially for higher deciles. This is consistent with a job ladder, where workers switch jobs when they find a better offer. Workers who stay at the same firm, perhaps those in collective bargaining units, also experience high growth. However, at the cross-section median growth remains low, reflecting wage dynamics of job losers and precarious work.

As an aside, there is an interesting finding here for the literature on South African wages which may be worth exploring in further work. What explains this difference in median wage growth for workers who are continuously employed versus workers as a cross-sectional distribution? The proportion of hires from non-employment is extremely high, about 64%, and there is a wage penalty associated with unemployment. This also affects the AKM estimation, as noted in the main text. Thus, the 0.27% growth rate at the cross-sectional median can be decomposed into a large positive growth rate for those who stay in employment, and a negative growth rate for those who do not (this also includes workers entering the labor force at lower wages than workers who leave, as expected from life cycles).

Table B3: **Individual wage growth by separation status**

	Workers	Real wage growth (p50)			
	(freq p.a.)	(all)	(Dec. 1-4)	(Dec. 5-8)	(Dec. 10)
Stayer	2,220,000	3.13%	2.34%	3.27%	3.38%
E-E sep	2,460,000	4.15%	-0.69%	5.46%	6.69%
Cross-section	8,844,562	0.27%	1.49%	1.36%	1.54%

Notes. Stayers are workers who remain at the same firm for the full period. E-E sep are workers who are employed for the full period but separate to a different firm at some point. Cross-section is the cross sectional wage growth by year. The lower overall median for the cross-section reflects South Africa's U-shaped percentile growth – higher growth at the top and bottom, and lower growth in the middle. Deciles are categorized by year. Workers are limited to those at firms with more than 20 employees. Source: Own calculations, South African tax records, 2011-2016.

C Appendix: Validation of AKM specification

I implement several further checks on the structure of the AKM equation 1 in the main text. Firstly, the residuals should have mean zero conditional on worker and firm effects ($E[\upsilon_{ijt}|\alpha_i, \phi_j, X_{ijt}\rho] = 0$). Figure C1 shows the median residuals by deciles of firm and worker effect for workers who move across firms. The AKM additive structure fits poorly at the bottom decile of the worker and firm effects distributions — but otherwise, the residuals are negligible in magnitude (0-2% of wages), especially in comparison to the magnitude of the changes in firm wage premia suggested by the Figure 1 event study in the main text. The poor fit at the bottom of the distribution may be explained by minimum wages, as pointed out by Card et al. (2018) in reference to a similar pattern in Portugal.

Secondly, limited mobility bias is a key concern in this literature. As recommended by Kline, Saggio, and Sølvsten (2020), I use as my primary set of estimates for the firm wage premia their leave-out estimator which corrects for the mismeasurement of the firm effects. The issue is that mis-measurement of the firm effects spuriously increases its variance, which is important when estimating the proportion firms account for in the total wage variance. Lamadon, Mogstad, and Setzler (2022) show that the firm wage premia are more likely to be mismeasured with fewer movers, and so in unreported robustness I restrict another set of leave-out estimated premia based on a set of firms with at least ten movers in each year (with similar results). I follow Lamadon, Mogstad, and Setzler (2022) and show in Figure C2 that the variance of the firm wage premia increases when estimated on smaller shares of movers within each firm. Note however that the variance shows little movement once 60% or more movers are included. This is consistent with the analysis in Lachowska et al. (2020), who use administrative data from Washington to argue that limited mobility bias is less of a concern when using longer time series; my six-year panel therefore gives some confidence. I also run the procedure provided by Gaure (2014) as a parametric correction, again with similar results.

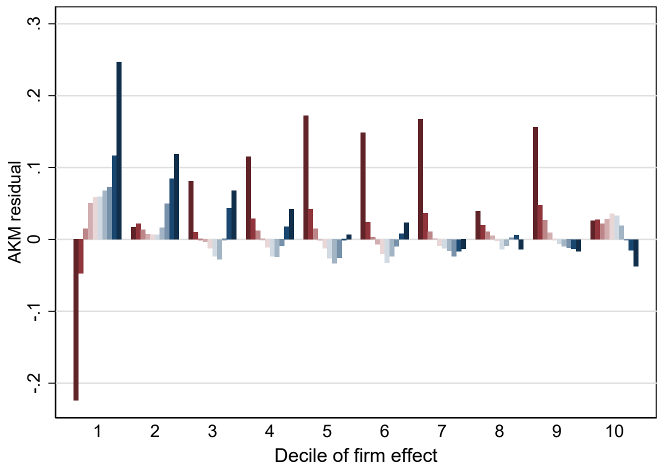
Thirdly, as discussed in Abowd, McKinney, and Schmutte (2019), the event analysis in the Figure 1 event study in the main text may still be consistent with some endogenous mobility which biases the firm wage premia. If wages depend on idiosyncratic firm-worker matches, and workers who are at badly matched firms tend to move towards firms that offer better matches, then firm wage premia will be overestimated.[36] Reassuringly, Bonhomme, Lamadon, and Manresa (2019) find using Swedish matched data that endogenous moves make little difference to their firm wage premia decompositions, despite strongly detecting the existence of such moves. Nevertheless, one strategy to address this is restricting the AKM sample of workers to separations from firm closings (to any firm) as an alternative set of firm wage premia. These separations are plausibly less endogenous, yet exhibit very similar estimates to the main set of firm wage premia. Moore and Scott-Clayton (2019) similarly consider firm wage premia for displaced workers, using matched administrative data from Ohio in the United States. Across my sample period, about 10,000 firms are not observed in the following year, and workers separate from these firms to a large network of firms. I provide estimates of the wage premia using this approach in the main text, Table 2. A weakness of this approach is that some observed closures may in fact reflect other events such as mergers.

Fourthly, I investigate the possibility that compensating differentials offset the wage premia with non-wage amenities (Lamadon, Mogstad, and Setzler 2022; Sorkin 2018). Since I observe different sources of income for wages in the tax data, I can compare the monthly wage to the total compensation package (including annual bonus, medical aid and overtime). If amenities offset wages in the firm premia, we would also expect the "total compensation" premia to be more compressed than the "monthly wage" premia.[37] The small role of amenities is affirmed by Figure C3, which shows the difference between the earnings and wage firm effects (a proxy for wage amenities) against the wage firm effects – there is no apparent pattern (slope of 0.07, standard error 0.14). While wage amenities do not reflect general amenities, this evidence does suggest that the wage premia may represent actual differences in firm value.

[36] With mean-zero match effects, relative firm wage premia can be estimated as the average wage change for workers who move between two firms. However, if movers earn a below-average income at the original firm (negative match effect), or are attracted to an above-average income at the destination firm (positive match effect), then the wage change will over-estimate the firm effect.

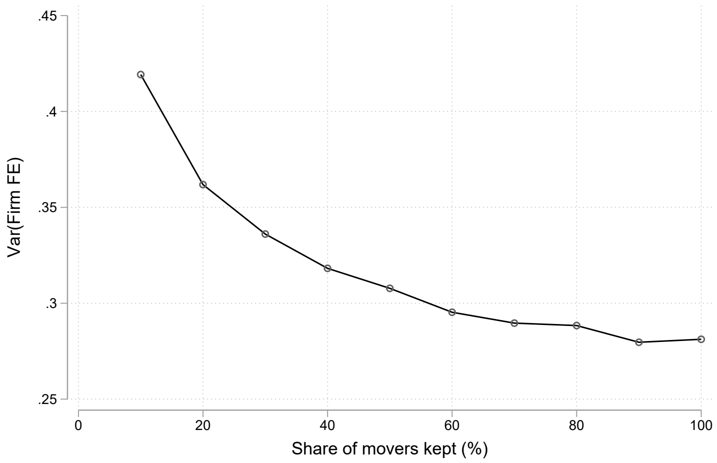
[37] Figure C3 initially suggests that this may be the case, with a slope of 0.93 indicating that an increase in monthly wage premia is accompanied by less than a 1:1 increase in total compensation premia. However, the estimate may purely be a result of measurement error attenuation; and in fact the reverse regression suggests this is the case. Without measurement error, the coefficient in the reverse regression should be the inverse, i.e. 1.08, yet the actual coefficient from the regression of wage on compensation is 0.9.

Figure C1: **AKM residuals by worker and firm deciles**



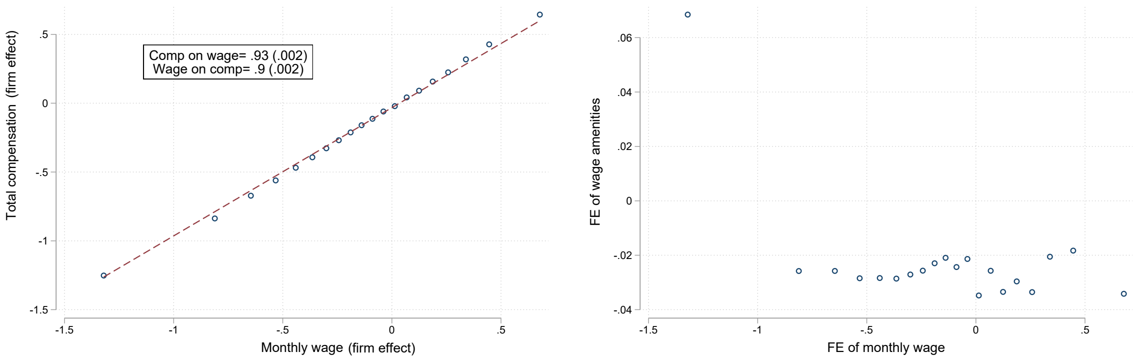
Notes. Residuals are calculated from the AKM regression on worker and firm effects, as well as year dummies and age controls. Deciles of worker effects are plotted in increasing order by decile of firm effect (dark red is the lowest worker effect, dark blue is the highest). Workers are limited to separations to employment from connected firms with more than 20 employees. Source: Own calculations, South African tax records, 2011-2016.

Figure C2: **Variance of Firm FE by share of movers included**



Notes. An AKM regression is run for samples with increasing proportion of movers retained. Movers (workers who move firms) are randomly selected and dropped so that each firm only retains the given share of movers. Var(Firm FE) is the variance of the resulting firm fixed effects, estimated without limited mobility bias correction. Workers are limited to those who separate from firms with more than 20 employees. Source: Own calculations, South African tax records, 2011-2016.

Figure C3: **Compensating differentials**



(a) **Total earnings and wages** (b) **Amenities and wages**

Notes. Total compensation includes medical aid, overtime, bonus, share options and other monetary compensation. Monthly wage includes only income categorized as monthly income. The regression of compensation on wage and the reverse regression are both reported to highlight measurement error. Workers are limited to those at connected firms with more than 20 employees. Source: Own calculations, South African tax records, 2011-2016.

D Appendix: Models

D.1 Framework details

This section provides lays out a few more details of the framework in the main text, focusing on the model (and leaving out much of the discussion). This is a simple partial equilibrium model meant to guide the empirical analysis.

My only substantive departure from Card et al. (2018) and Dickens, Machin, and Manning (1999) is the inclusion of the worker-type productivity effect A_i, which simply generalizes the two-type setup in Card et al. (2018) for close analogy to worker wage premia. Many of the assumptions follow Card et al. (2018). Firstly, wages are assumed to be set by employers to maximize profits, subject to constraints on the relationship between wages and the supply of labor. Secondly, I assume that, given the labor supply constraint, firms are only aware of the *shape* of the curve and cannot set wages so as to wage-discriminate on an individual worker basis. Thirdly, firms hire any worker (of the given type) who is willing to accept a job at the posted wage. I do not model substitution across worker types. Fourthly, for simplicity I ignore capital and intermediate inputs.

Unlike Card et al. (2018), I provide no explicit micro-foundation for the critical parameter ε, the firm labor supply elasticity. I could follow the approach in Card et al. (2018), such that jobs are static differentiated products which workers value through a utility term associated with wages and an idiosyncratic utility term drawn from a Type 1 extreme value distribution. Workers are fully informed about job opportunities. This is then transformed into a logit choice probability, which together with a large number of firms yields a simple firm labor supply elasticity constraint. However, I rather take ε as given, as in Dickens, Machin, and Manning (1999), which has the disadvantage of being opaque on its source but the advantage of not taking a strong position on its source (for example, alternatively search frictions could be the source).

To characterize the firm problem and optimal wage: Firm j faces downwards sloping firm-specific product demand parameterized by η, and has exogenous productivity for each worker type i equal to a firm term T_j times by a worker type term A_i. For example, production is given by $Y_{ij} = \frac{\eta}{\eta-1} A_i T_j N_{ij}^{1-1/\eta}$ for $N_{ij}(w_{ij})$ the number of workers of type i at firm j. Firms maximize profit by setting the wage w_{ij} for each worker type i, $\max_{w_{ij}} \pi_{ij} = \frac{\eta}{\eta-1} A_i T_j N_{ij}^{1-1/\eta} - w_{ij} N_{ij}$ subject to an upwards sloping firm labor supply constraint, $N_{ij} = w_{ij}^{\varepsilon_j}$ with firm-specific labor supply elasticity ε_j.

The marginal cost of labor to the firm is given by $(1/\varepsilon_j) ln(N_{ij}) + ln(1 + 1/\varepsilon_j)$, and marginal revenue product of labor is equal to $ln(A_i) + ln(T_j) - (1/\eta) ln(N_{ij})$; see Manning (pp. 338-341 2003b) for the same derivations. Then, setting these equal to each other, employment and wages are given by:

$$ln(N_{ij}) = \frac{\varepsilon_j \eta}{\eta + \varepsilon_j} ln(A_i) + \frac{\varepsilon_j \eta}{\eta + \varepsilon_j} ln(T_j) + \frac{\varepsilon_j \eta}{\eta + \varepsilon_j} ln(\frac{\varepsilon_j}{1 + \varepsilon_j})$$

$$ln(w_{ij}) = \frac{\eta}{\eta + \varepsilon_j} ln(A_i) + \frac{\eta}{\eta + \varepsilon_j} ln(T_j) + \frac{\eta}{\eta + \varepsilon_j} ln(\frac{\varepsilon_j}{1 + \varepsilon_j}) \tag{6}$$

Where the wage equation substitutes the firm labor supply constraint, $ln(N_{ij}) = \varepsilon_j ln(w_{ij})$, into the optimal employment equation.

A few caveats apply to this equation. Firstly, in the more general case ε_j varies by firm. An example of a firm-specific ε_j is given by the case of the simple logit model (McFadden et al. 1973), $\varepsilon_j = \varepsilon(1 - s_j)$ for firm employment share s_j. Of course, ε_j could also be specific to both the firm and the worker as in ε_{ij}. In the main text, I focus on the constant-elasticity $\bar{\varepsilon}_j = mean(\varepsilon_j)$, for expositional clarity as this simplifies the variance terms considerably. Secondly, firms may vary wages for other reasons not captured in the production function or in the profit-maximization (e.g. Burdett and Mortensen 1998), but my aim here is to provide a comparable setup to the literature. In particular, this approach ignores efficiency wage explanations for firm wage premia, which can emerge e.g., as a result of monitoring problems. Thirdly, this framework also has no complementarities in worker and firm productivity, i.e. no "match effects", as assumed by the AKM model, in contrast with for example Lamadon, Mogstad, and Setzler (2022). This simplifies the setup and framework discussion, but has the disadvantage of not directly allowing a mechanism towards sorting.

Taylor approximation of relevance of heterogeneity in ε_j

The framework section in the main text outlines how firm wage dispersion is influenced by productivity dispersion and by the firm labor supply elasticity. For the firm labor supply elasticity, I left one channel – heterogeneity in the elasticity – for further discussion here of approximate effects.

The variance in the pass-through coefficient $\frac{\eta}{\eta+\varepsilon_j}$ will be one source of higher firm wage dispersion, but is likely to have limited effect. A second-order Taylor approximation of $f(\varepsilon_j) = \frac{\eta}{\eta+\varepsilon_j}$ evaluated at $\bar{\varepsilon_j}$ suggests $var(f(\varepsilon_j)) = \frac{\eta^2}{(\eta+\bar{\varepsilon_j})^4} var(\varepsilon_j)$, which for $\eta = 5$ and $\bar{\varepsilon_j} = 2$, gives 0.01 multiplied by $var(\varepsilon_j)$. This is likely to be small, as consider $var(\varepsilon_j) = \bar{\varepsilon_j} = 2$ with $\eta = 5$, then the variance is only 0.02. To complete the argument, we need to consider that this coefficient interacts with each term. The Taylor approximation of the variance of the product of two random variables, $x = \frac{\eta}{\eta+\varepsilon_j}$ and $y = ln(T_j)$, is given by $\bar{y}^2 var(x) + 2\bar{x}\bar{y}cov(x,y) + \bar{x}^2 var(y)$. The first term is negligible (given the previous approximation of $var(x) = var(f(\varepsilon_j))$, while also noting $\bar{y}$ is normalized to zero), and there is some dependence on the covariance (though again note $\bar{y}$ normalized to zero). The third term remains as discussed in baseline case of the constant-elasticity, which has a large effect depending on $var(ln(T_j))$.

The variance of the firm labor supply elasticity will also affect the third term in the main text Equation 2, i.e. $\frac{\eta}{\eta+\varepsilon_j} ln(\frac{\varepsilon_j}{1+\varepsilon_j})$. A second-order Taylor approximation of $g(\varepsilon_j) = ln(\frac{\varepsilon_j}{1+\varepsilon_j})$, once again evaluated at $\bar{\varepsilon_j}$, suggests $var(g(\varepsilon_j)) = \frac{1}{(\bar{\varepsilon_j}(1+\bar{\varepsilon_j}))^2} var(\varepsilon_j)$, which for $\bar{\varepsilon_j} = 2$, gives 0.03 times $var(\varepsilon_j)$. Once again, this may be small, as consider $var(\varepsilon_j) = \bar{\varepsilon_j} = 2$, then the variance is only 0.06. To account for the pass-through interactions with this term, let $x = \frac{\eta}{\eta+\varepsilon_j}$ and $y = ln(\frac{\varepsilon_j}{1+\varepsilon_j})$ in the Taylor approximation above. Then for $var(\varepsilon_j) = \bar{\varepsilon_j} = 2$ and $\eta = 5$, $var(\frac{\eta}{\eta+\varepsilon_j} ln(\frac{\varepsilon_j}{1+\varepsilon_j})) \approx -.024$ which is once again small (it is driven by the negative covariance between $\frac{\eta}{\eta+\varepsilon_j}$ and $ln(\frac{\varepsilon_j}{1+\varepsilon_j})$).

Overall, the Taylor approximations suggest that variance in ε_j plays a limited role in the variance of wages given by Equation 2 in the main text.

D.2 Firm wage inequality and development

The following toy model is intended to provide some intuition as to a simple dynamic between development and firm wage inequality, proceeding from the assumption of a finite firm labor supply elasticity. Initially, at the onset of industrialization, a small portion of firms have high productivity and this attracts a set of workers. Higher productivity firms optimally pay higher wages along the upwards sloping firm labor supply curve. With most workers in low-productivity work, wage inequality is initially low; as industry develops and employment in the higher productivity sector increases, wage inequality first increases and then declines.

The analysis is in the spirit of Kuznets and Lewis, but the mechanisms explicitly operate through optimal firm wage-setting derived from monopsony power. The mechanism yields two insights. Firstly, the rise and fall of wage inequality across the transition from low to high productivities still occurs in a multi-firm setup. Secondly, the firm wage premium is derived through the wage pass-through from higher productivity, which follows from a finite labor supply elasticity; unlike the wage premium in classical models, where the premium is assumed.[38] Some implications that follow from this mechanism are that the arc of wage inequality may be legislated against (as in the case of collective bargaining and minimum wages), and that the speed of transition towards the industrialized sector may be substantially slowed down.

Firm wage-setting

Assume the labor supply to the firm $\varepsilon_{LS} = \partial lnL_j / \partial lnw_j$ is less than perfectly elastic. As Manning (2003) illustrates, this may be derived in various ways, such as from a cost of training and recruitment that increases with firm size, or from a fixed offer probability received by workers per firm. I use a simpler production function than in the main framework above, for expositional purposes:$Y_j = A_j L_j$, and profits $\pi_j = Y_j - w_j L_j$, profits are maximized by the firm setting wages which are given optimally as:

$$w_j = A_j \frac{\varepsilon_{LS}}{1+\varepsilon_{LS}} \tag{7}$$

[38] Other mechanisms have derived the wage premium under weaker assumptions, such as the labor turnover model of Stiglitz.

Wages are therefore set higher for higher firm productivities, unlike in the case of firms as wage-takers. For example, in classical models wages are set at a reservation wage (usually with an assumed premium) following from a perfectly elastic labor surplus.

Two-sector statics

Assume there are two sectors, one high productivity sector often termed the modern sector M in classical development models, and a low productivity sector referred to as the subsistence sector S. To be clear, S may refer to a range of scenarios, including actual rural subsistence, unemployment, informal work, or a sector with inferior technology.[39] Sector S faces similar constraints as sector M, except at a lower productivity.[40]

The variance of log wages in this economy is as follows:

$$var(ln(w_j)) = (1-s)\sigma_M + s\sigma_S + s(1-s)(\mu_M - \mu_S)^2 \tag{8}$$

where subscripts indicate the sector, s is the proportion of labor in sector S, σ_k denotes the variance of wages in sector k, and μ_k denote mean wages in sector k.

Dynamics

I model the transition between sectors S and M by following Aghion, Caroli, and Garcia-Penalosa (1999).

They model the industrialization process as the randomized take-up of the modern sector technology, depending on a random arrival process γ of exogeneous adoption and being surrounded by at least k modern sector firms out of m total neighbors. Whereas their model focuses on skilled versus unskilled labor, I focus on firm wages as above.

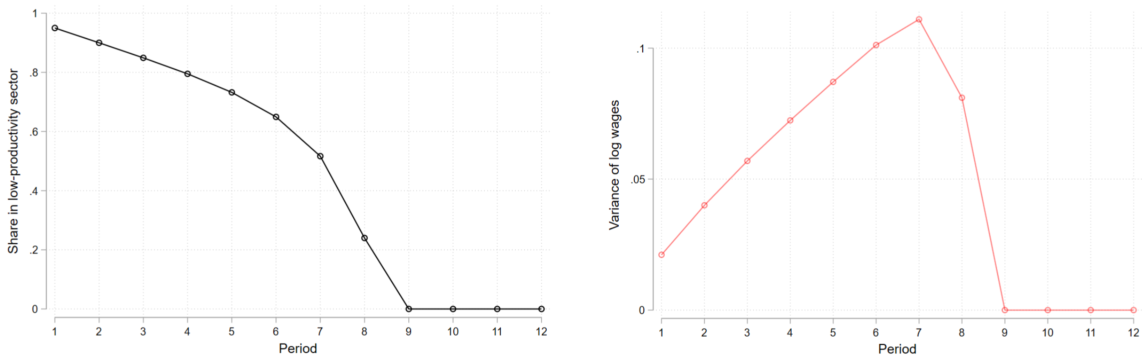
The change in s, i.e. adoption of modern technology, is determined by:[41]

[39] For simplicity, I do not model the goods sector (alternatively I assume a competitive open goods market), though Ros (2013) suggests interesting dynamics in the interaction of the goods and labor markets.

[40] Alternative assumptions also work, such as a competitive subsistence sector or an average marginal product, as long as the productivity is substantially lower.

[41] As an alternative, we can incorporate the firm labor supply elasticity ε_{LS} in as follows. Assume that technology transfer occurs through worker transitions and learning-by-doing. Then the rate that firms adopt the new technology depends on the firm labor supply elasticities. This however requires a flow of workers from high-wage M sector firms to low-wage S sector firms.

Figure D1: **Simulation of firm wage inequality as high productivity technology spreads**



(a) **Share in low-productivity** (b) **Variance in wage premia by LSE**

Notes. Panel A depicts the share in the low productivity sector S as opposed to the high productivity sector M over time. I use the values $\gamma = 0.4$, $k = 3$, $m = 5$ in Equation 9, and a firm labor supply elasticity of $\varepsilon = 2$ for Equation 7.

$$s_{t+1} = s_t - \gamma - (1 - s_t)\left(\sum_{j=k}^{m} \binom{m}{j} (1 - s_t)^j s_t^{m-j}\right) \tag{9}$$

Combining equations 7, 8 and 9, the variance of wages evolves as the modern sector spreads. In the simple case of $\alpha = 0$, and letting the productivities differ by a factor of 2, $A_M = 2$, $A_S = 1$ (with equal variance of 1), there is a wage arc. Figure D1 illustrates this. Initially, very few firms have the modern sector technology. As time passes, and surrounding firms learn, sector M grows and this increases total wage inequality as the population-level between-sector gap grows. However, as the modern sector technology passes half of the population, wage inequality declines again.

E Appendix: Matched mover event-study

These estimates follow the event-study approach in Bassier, Dube, and Naidu (2022), henceforth BDN. An event-study panel is constructed as follows. All Employment to Employment (E-E) separators in the year 2013 are isolated, along with these workers' surrounding annual records (a maximum of 2008 to 2018). The sample is further restricted to workers who were at the same "Origin Firm" in 2012 as in 2013. Event-time is indexed such that 0 indicates 2014, i.e. pre-periods are at the Origin Firm and post-periods are at the Destination Firm.

E.1 First stage: Firm wage variation

Firm average wages are estimated for Destination Firms based on stayers, i.e. excluding workers who are hired or separate in each year. The first stage regression consists of the change in a worker's wage across the Origin and Destination Firms as the outcome, and the change in firm average wages as regressor (Equation 10). The primary benefit of this approach is that interacted fixed effects $L(history_{i,t})$ can transparently be included to control for confounders, unlike for AKM, such that estimates compare workers matched on these characteristics. By comparing the change in own wage $(w_{i,D(i),t} - w_{i,O(i),t-1})$ to change in firm wage $(\bar{w}_{i,D(i),t} - \bar{w}_{i,O(i),t-1})$ for finely matched workers who leave the same Origin firm O towards different Destination firms I, this approach measures how much of the variation in own wage across firm switches is due to differences in firm wage policies.

$$w_{i,D(i),t} - w_{i,O(i),t-1} = \phi(\bar{w}_{i,D(i),t} - \bar{w}_{i,O(i),t-1})(f_{D(i),t} - f_{O(i),t-1}) + L(History_{i,t,d}) + \varepsilon_{i,t} \quad (10)$$

In brief, this matches workers who leave the same firm at the same time with similar characteristics (wage, tenure, age, gender), and compares the change in their respective wages relative to the changes in average firm wages at the new firms. While this approach is most suited to estimating the separations elasticity (see next section), it also measures as a first stage how much of the variation in own wages across firm switches is due to differences in firm wage policies (see also Finkelstein, Gentzkow, and Williams 2016). The advantages over the AKM structure are that this approach allows a much richer set of controls regarding worker histories, and also does not require constant firm wage premia for all workers in a firm.

Figure E1 shows a flat pre-trend, which is an anologous falsification check on the exogeneity assumption of the destination firm wage as in Figure 1 of the main text. The wage trend after the move is also stable, indicating that concerns such as tenure profiles are not important.

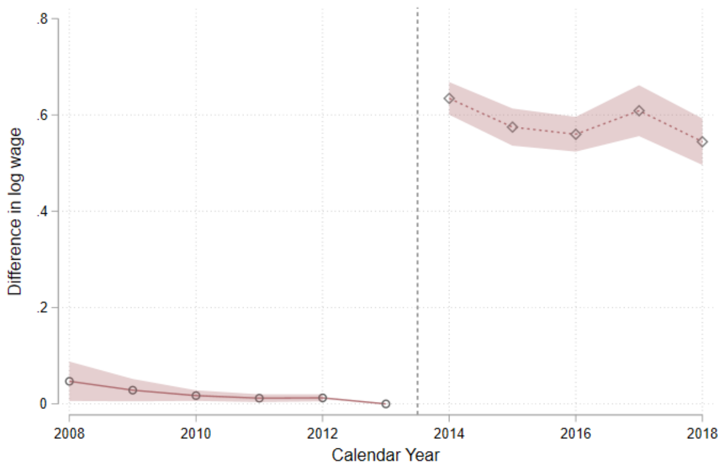


Figure E1: **First stage: Difference in log wage on difference in firm average wages**
Notes. See Appendix D for sample construction and specification details. The regression includes fixed effects for Origin firm, salary bins (12), fraction of year employed in bins (8), tenure bins (3), gender bins (2), and age bins (8). Origin firms are restricted to a firm size of at least 20 workers. The difference in individual and firm wages are censored at the 1% tails. Observations are restricted to Origin firm (before the event) and Destination firm (after the event).

Row 1 of Table E1 presents results from this first-stage regression using specifications with increasing controls. The unconditional coefficient is 0.53 (column 1), and this increases to 0.56 when conditioning on the same Origin firm. The preferred estimate of about 0.65 compares workers leaving the same firm in the same year, earning similar wages, having been at the firm for similar tenure, and sharing demographic characteristics of gender and age (columns 3-7). With industry controls the first stage coefficient is even higher (0.73, column 8), but this may be a bad control in the sense that choice of industry is within the causal pathway. The coefficient of 0.65 from this regression of change in own wage on change in firm wage is high compared to Bassier, Dube, and Naidu (2022), who use an identical design to find an estimate of 0.32 for Oregon, USA.[42] That is, two thirds of the variation in the wages of closely matched workers

[42]This is comparable to the KSS-based estimate, which decomposes the total wage variation into 30% firms, 9% covariance, 40% workers, and 21% residual. Since the movers approach compares similar workers, it removes

across firm switches is due to differences in firm wage policies in South Africa.

E.2 Second stage: Labor supply elasticity

BDN develop this approach to measure the firm labor supply elasticity from worker re-separations as follows. The equation above forms the first stage of an instrumental variables regression. The reduced form has an indicator for worker separation from the *Destination* firm in period $t+k$ as the outcome ($s^D_{i,t+k}$), and the change in average firm wage $(\bar{w}_{i,D(i),t} - \bar{w}_{i,O(i),t-1})$ as regressor. Identification arises from comparing matched workers from the same Origin firm who separate to different Destination firms, each being treated with a different average firm wage at their Destination firm, and this leads to correspondingly different separation rates.

$$s^D_{i,t+k} = \delta(\bar{w}_{i,D(i),t} - \bar{w}_{i,O(i),t-1}) + L(History_{i,t,d}) \times \mathbf{1}_{t+k} + \varepsilon_{i,t+k} \tag{11}$$

Table E1, column 1, shows the implied labor supply elasticity estimate of 0.8 using the *unconditional* change in wages is very similar to the main AKM estimate of about 0.9. Adding fixed effects progressively increases this estimate, with a labor supply elasticity based on the separations elasticity in the range of 1.3 to 1.6. Comparing workers who leave the same Origin firm in the same year yields an elasticity of 1.3 (column 2), adding wage, tenure and demographic controls increases this to 1.4 (column 3), adding further covariates hardly changes this estimate (column 5), and adding prior wage growth of the worker in the pre-period increases this to 1.6 (column 6).

Including industry controls increases the estimate to 1.8, but once again it is unclear if this is a good control to include. The elasticity based on E-E separations is higher, for the corresponding controls (columns 4 and 7), which is in line with the discussion in the main paper.

As for BDN, my preferred estimate of 1.6 is higher than my AKM estimate. Relative to Oregon where the estimate is $\varepsilon_{LS} = 3$ using earnings as in BDN, this estimate for South Africa is low – consistent with the claim in this paper that South Africa has relatively high

the worker and covariance terms. The comparable KSS magnitude is therefore $.3/(.2+.21) = 0.59$, which is very close to the movers estimates of 0.65.

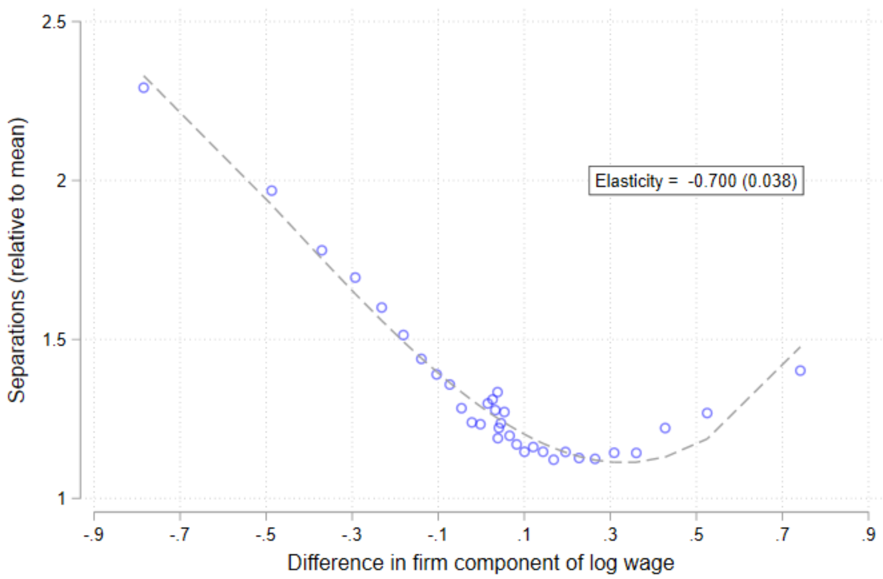
Table E1: **Separations estimates**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
First stage	0.534	0.562	0.645	0.646	0.700	0.643	0.645	0.729
	(0.015)	(0.011)	(0.014)	(0.015)	(0.017)	(0.017)	(0.018)	(0.043)
IV estimate	-0.399	-0.628	-0.713	-0.948	-0.720	-0.794	-1.073	-0.896
	(0.021)	(0.019)	(0.043)	(0.059)	(0.048)	(0.055)	(0.074)	(0.083)
Implied LSE	0.8	1.26	1.43	1.9	1.44	1.59	2.14	1.79
	(0.042)	(0.038)	(0.086)	(0.12)	(0.096)	(0.11)	(0.15)	(0.17)
Obs	0.582	0.580	0.501	0.437	0.282	0.480	0.419	0.225
Movers	268445	267090	189845	164077	101104	170670	147387	76218
Fstat (IV)	1068	2058	1556	1269	1050	920	715	262
E-E seps				Y			Y	
Interacted controls								
Year	Y	Y	Y	Y	Y	Y	Y	Y
$\times$ Firm		Y	Y	Y	Y	Y	Y	Y
$\times$ Wage $\times$ tenure			Y	Y	Y	Y	Y	Y
$\times$ Covariates			Y	Y	Y	Y	Y	Y
$\times$ Add. covariates					Y			
$\times$ Prior wage growth						Y	Y	
$\times$ Dest. industry								Y

Notes. Covariates refer to gender bins (2), and age bins (8). Additional covariates refer to annual bonus bins (8) and wage bins exclusive of benefits (8). Origin firms are restricted to a firm size of at least 20 workers.

monopsony power. The instrumental variables relationship between change in firm average wage and separations is shown in figure E2.

Figure E2: **Instrumental variables bin scatter of separations on difference in firm average wages**



Notes. The regression includes fixed effects for Origin firm, salary bins (12), fraction of year employed in bins (8), tenure bins (3), gender bins (2), and age bins (8). It also includes a control for worker skill, as proxied by the AKM worker fixed effect. Origin firms are restricted to a firm size of at least 20 workers. The difference in individual and firm wages are censored at the 1% tails. The instrumental variables regression is implemented using the control function approach.

F Appendix: Firm rent-sharing elasticity

F.1 Estimation framework

In models of monopsonistic labor markets, rent-sharing is an optimal wage-setting outcome (Card et al. 2018; Lamadon, Mogstad, and Setzler 2022). Firms with higher marginal revenue product (or rents) gain more from employing more workers, which requires increases in the wage to attract more workers. Since wages are more sensitive to firm-specific rents in more monopsonistic markets (see framework above), the relatively low estimated firm labor supply elasticity suggests a high rent-sharing elasticity.

In this section, I estimate the passthrough coefficient on firm productivity to firm wage premia, also known as the rent-sharing elasticity (ε_{rent}). I follow the literature in using value added per worker as a proxy for these "quasi-rents". My main specification follows Card, Cardoso, and Kline (2016) in regressing the estimated firm wage premium ϕ_j on log firm value added per worker (VA_j), with controls X_j for time, industry and location.

$$\phi_j = \alpha + \varepsilon_{rent} ln(\text{VA}_j) + \Gamma X_j + r_j \tag{12}$$

The estimation equation is in essence a firm-level and cross-sectional. However, following Card, Cardoso, and Kline (2016), I run this at the invidiual level while appropriately clustering at the firm level. The results are very similar when running at the firm level.

Assuming as in the AKM model that individual wages can be decomposed into an *invariant* worker effect and a firm effect, any *firm specific* effect should reflect as differences in the firm component of the wage. The earlier literature on rent-sharing tended to use wages as the outcome, which yielded an upwardly biased rent-sharing coefficient since more profitable firms tend to employ more workers with higher invariant worker effects. Wages are then higher due to selection on worker effects *as well as* rent-sharing. The AKM firm wage premium effectively controls for individual characteristics, including unobservables. To illustrate the bias, I also estimate the Equation 12 using log firm average wage instead of the estimated firm wage premium.

Omitted variables correlated with profits and the firm wage premia may still bias the results.

As an alternative specification that also does not rely on the estimated firm wage premia, I use a differenced equation as follows:

$$ln(w_{j,t}) - ln(w_{j,t-s}) = \alpha + \varepsilon_{rent}(ln(VA_{j,t}) - ln(VA_{j,t-s})) + \Gamma X_{j,t} + e_{j,t} \tag{13}$$

Equation 13 shows the change in log firm average wage, the change in log firm value added per worker, and controls which vary by firm and time. I run this at the firm by year level, weighted by firm size and clustered by firm. The source of variation in Equations 12 and 13 are different, allowing us to assess sensitivity to method. Identification in a differenced setting also includes incumbent workers rather than just the movers used to estimate the wage premia in AKM. One challenge is that annual movements in value added are subject to measurement error, for example adjustments to the balance sheet related to asset purchases rather than actual profits. I therefore use as a baseline one period difference ($s = 1$), but supplement this by taking longer differences ($s = 3$) following Griliches and Hausman (1986). This reduces measurement error by increasing the signal-to-noise ratio in the differenced regressor. I also include fixed effects for industry by location to isolate variation from firm-specific shocks as opposed to market level shocks.

F.2 Estimates of rent-sharing

Firm wage premia increase strongly with firm rents. The associated rent-sharing elasticity is high relative to other industrialized countries, and this variation in value added per worker explains about 25% of the total variance in firm wage premia. Across the distribution of log firm value added per worker, there is a strong linear relationship with log wages (Figure F1).

Table F1 presents estimates of the rent-sharing elasticity, all demonstrating a strong correlation with p-values below 0.001. Column 1 shows an elasticity of 0.3 using the raw wage, which is upwardly biased since high wage workers tend to locate at high value added firms. This is also confirmed by a direct regression of the worker wage premia on log value added, with a coefficient of 0.12 suggesting positive sorting. Using the firm wage premia instead of raw wages, the coefficient is 0.14 (column 2), and similarly when restricting to firm wage premia estimated

Figure F1: Non-parametric scatter of firm wage premia and log value added per worker

Notes. Firm average wage refers to directly recorded wages for each worker, and are centered around 0 for plotting. Firm fixed effects are estimated using the AKM regression. The plot is generated from firm-level data weighted by number of workers and limited to connected firms with more than 20 employees.

from firm closings (column 3).

	(1)	(2)	(3)	(4)	(5)	(6)
ln(VApe)	0.301	0.141	0.140	0.141	0.191	0.171
	(0.011)	(0.008)	(0.010)	(0.036)	(0.039)	(0.024)
Obs	28 mill.	26 mill.	26 mill.	127,289	66,832	66,532
R^2	.21	.25	.21	.13	.23	.336
log(wage)	Y			Y	Y	Y
Firm FE		Y	Y			
All firms		Y				
Closings			Y			
First diff.				Y		
Long diff.					Y	Y
Market × Year FE						Y

Table F1: Rent-sharing elasticities

Notes. VApe is value added per employee as a proxy for rent, calculated as sales minus non-labor expenses. Firm FE refer to the estimated AKM firm wage premia from section 3, repectively estimated off of the full sample (“all”) and the sample of workers from firm closings (“Closings”). The final 3 specifications are run at the firm-level (weighted by number of workers), comparing differenced outcomes within firms over time. The long difference ($lnva_t - lnva_{t-3}$) is taken over three periods. Market FE refer to industry by location fixed effects. Workers are limited to connected firms with more than 20 employees. Standard errors are given in parentheses. Source: Own calculations, South African tax records, 2011-2016.

The first-differences specification is again similar with an estimate of 0.14 (column 4).

However, adjusting for measurement error by taking the long difference across time periods increases the coefficient substantially to 0.19. To ensure this is not driven by industry-level adjustments, I control for market-level differences (Lamadon, Mogstad, and Setzler 2022). The estimate rent-sharing elasticity is robust to this control, giving my preferred estimate of 0.171 (standard error of 0.024).

Table F2 provides further robustness. The AKM estimates are similar when using gross profits as a measure of rent instead of value added (elasticity of 0.12), or total factor productivity as proxied by the residual of a regression of sales on cubics in firm size, assets and material costs (elasticity of 0.14). Winsorizing or adding market fixed effects reduces the estimate slightly to 0.11. Focusing on the wages of hires only increases the estimate to 0.16.

Table F2: **Alternative specifications for rent-sharing elasticity**

	(1)	(2)	(3)	(4)	(5)
ln(Rent)	0.123	0.143	0.112	0.115	0.159
	(0.008)	(0.020)	(0.007)	(0.006)	(0.042)
Rent measure					
Value Added			Y	Y	Y
Profit	Y				
TFP		Y			
Winsor			Y		
Market FE				Y	
Firm First Diff					Y
Hires only					Y
Obs	2.52e+07	2.18e+07	2.83e+07	2.61e+07	103197

Notes. Rent is the regressor, measured as indicated by value added per employee (sales minus non-labor costs, per worker), profit per worker (sales minus non-labor costs and labor costs), or total factor productivity (calculated as the firm effect residual from a regression of sales on cubic terms in firm size, assets, intermediate expenses and year effects). Winsor indicates the firm wage premia are winsorized at the 5 percent tails. Market FE are industry by geo fixed effects, i.e. 20 by 221 categories. The final specification is run at the firm-level in first-differences, where the outcome is the average wage for new hires only. Workers are limited to those at connected firms with more than 20 employees. Source: Own calculations, South African tax records, 2011-2016.

Overall, these estimates are towards the upper end of the range found in the AKM rent-sharing literature of 0.05 to 0.15 (Card et al. 2018). They are consistent with the high firm wage dispersion and labor supply elasticities estimated above.

F.3 Appendix: Relating rent-sharing and labor supply elasticities

A broad class of models finds that rent-sharing increases in more monopsonistic markets. Intuitively, when markets are competitive, workers are close to their marginal product and firms can adjust on the employment margin only. Any wage premia quickly disappear as workers flow to the highest-paying firms and market wages adjust. In more monopsonistic markets, workers are paid further below marginal product and are unable to compete away wage markdowns. Firms-specific shocks can affect firm-specific wages more persistently as firms adjust on both the wage and employment margins. To illustrate this relationship between the rent-sharing elasticity (ε_{rent}) and the labor supply elasticity (ε_{LS}), I consider the simplest case and then compare three models proposed in the recent literature.

In the simplest case, a profit-maximizing firm with an upwards sloping labor supply curve has the profit function $\pi = pTQ(L) - wL(w)$, where T indicates productivity. The profit maximizing wage $w = \frac{\varepsilon_{LS}}{1+\varepsilon_{LS}}Tp$ implies a markdown on productivity of $\frac{\varepsilon_{LS}}{1+\varepsilon_{LS}}$ and a rent-sharing elasticity $\varepsilon_{rent} = \frac{\partial lnw}{\partial lnT} = 1$. Taking derivatives, the ε_{rent} is independent of the ε_{LS}, and the predicted $\varepsilon_{rent} = 1$ is much larger than the range of estimates in the literature to date, .05< $\hat{\varepsilon}_{rent} < .15$ (Card et al. 2018). However, we are interested in models which allow for firm-specific shocks, examples of which are given below.

In my framework in the main text, as in Card et al. (2018) and Manning (2003a, pp. 338-341), firms have downward-sloping firm-specific product demand. With $Y = \frac{1}{1+1/\eta}T_jN^{1-1/\eta}$ and $ln(w) = 1/\varepsilon ln(N_j)$, log marginal factor cost $(1/\varepsilon)ln(N_j) + ln(1+1/\varepsilon)$ equates to log marginal revenue $lnT_j + (1/\eta)ln(N_j)$, and the implied rent-sharing elasticity equation is $\frac{dln(w)}{dln(T_j)} = \frac{\eta}{\eta+\varepsilon}$, where η is the downwards-sloping firm-specific demand elasticity and ε is the firm labor supply elasticity. This implies $\frac{dln(w)}{dln(T_j)d\varepsilon} = -\frac{\eta}{(\eta+\varepsilon)^2} < 0$, meaning that the rent-sharing decreases with an increase in the firm labor supply elasticity.

A second model is proposed by Lamadon, Mogstad, and Setzler (2022), with parameters β, the standard deviation in idiosyncratic tastes for a firm; λ, an exogenous tax parameter; and ρ, the independence of tastes within a labor market. They model that the wage can be written as $w = \frac{1}{1+\frac{\rho}{\lambda\beta}}p$, where p is the marginal product of labor. Given the standard markdown equation, this implies that $\varepsilon_{LS} = \frac{\lambda\beta}{\rho}$. For estimating these parameters, they model that $\varepsilon_{rent} = \frac{1}{1+\frac{\lambda\beta}{\rho}}$

which implies that $\varepsilon_{rent} = \frac{1}{1+\varepsilon_{LS}}$. The ε_{rent} and ε_{LS} are negatively correlated – an equation very similar to and consistent with the previous model. Using their parametrization, my estimate of $\varepsilon_{rent} = 0.23$ implies $\varepsilon_{LS} = 3.3$; alternatively, my estimate of $\varepsilon_{LS} = 2$ implies $\varepsilon_{rent} = 0.33$. Additional constraints may reconcile these different predictions of the magnitudes of $\hat{\varepsilon_{rent}}$ and $\hat{\varepsilon_{LS}}$.

A third model can be derived from the multinomial logit, as in McFadden et al. (1973). Let the utility of workers be expressed as $V(w_j) = \beta ln(w_j) + \nu_{ij}$, where β parameterizes the latent monopsony power (i.e. the responsiveness of worker utility to wages), and ν_{ij} follows a Gumbel distribution indicating idiosyncratic preferences for the firm. The distribution yields the probability a worker is employed at firm j, or equivalently the firm share of j, in log terms $lnp_j = \beta ln(w_j) - ln(N)$ (assuming firms are atomistic). The optimal wage response is pinned down by the firm's wage-setting function. Firm's maximize profits $\pi_j = \max_{w_j} \frac{1}{1-\eta} T_j(p_j(w_j)N)^{1-\eta} - w_j \cdot p_j(w_j)N$, which yields the associated wage $lnw_j = \frac{1}{1+\eta\beta}(ln(\frac{\varepsilon_{jj}}{1+\varepsilon_{jj}}) + lnT_j)$. This is similar to the first model of Card et al. (2018), both derived from logit idiosyncratic preferences. The implied rent-sharing is $\frac{dln(w)}{dln(T_j)} = \frac{1}{1+\eta\beta}$, which as before is increasing in monopsony power.

This brief comparison of selected models illustrates the negative relationship between ε_{rent} and ε_{LS}, derived in a variety of ways. The exact functional forms of this negative relationship depends on the model, however, which serves as some motivation for the separate estimation of $\hat{\varepsilon_{rent}}$ and $\hat{\varepsilon_{LS}}$. Moreover, other constraints are likely to play a role. As an illustration, a crude calibration using the framework in this paper motivates a rent-sharing elasticity of $\frac{dln(wage)}{dln(MRPL)} = \frac{\eta}{\eta+\varepsilon}$, as in Card et al. (2018) and Manning (2003a), which depends on other parameters (η). Using $\eta = 3$ to $\eta = 10$ as in Card et al. (2018), and a firm labor supply elasticity of $\varepsilon = 2$, the implied range of the rent-sharing elasticity is between 0.6 and 0.83 — which is much higher than the empirical range reviewed in Card et al. (2018). (Of course, if η was closer to a half, that would rationalize the estimates in this paper.)

G Appendix: Wage premia and informality

G.1 Worker transitions across sectors

Given that the tax data are restricted to formal employment, I use survey data (Statistics South Africa 2010-2015). The survey design includes a 25% outrotation panel component, which allows me to link workers over time.[43] While the clear advantage is observing informal and unemployed workers, the main disadvantages relative to the tax data are a lack of firm identifiers (meaning I am unable to control for AKM firm fixed effects), and larger measurement error in wages.

I define a formal worker as any worker with a written employment contract, deductions for benefits (such as unemployment insurance, pension or medical aid), or deductions for income tax. The informally employed consist of all other workers. I separate out informal single-person business owners (identified as self-employed, employing no paid labor, and with no tax registration), as these are likely survivalist enterprises that simply subsist. Informal workers include paid workers in both formal and informal enterprises.

To set the context, Table G1 presents the frequency of workers by transition and sector. Out of every 10 economically active workers, 5 are formally employed, 2 are informally employed, and 3 are unemployed. The transitions indicate that informal sector workers are more likely to move out of their jobs than their formal sector counterparts. Panel A shows that formal employment is the most stable category, with 91% of formally employed workers remaining in their category by the following quarter, compared to only 65% of the informally employed. Nearly 1 in 5 workers transition from the informal to formal sector, compared to only 1 in 25 in the reverse direction.

Table G1 Panel B only considers workers who separate from their job. Note that quarterly job separations for workers in the formal sector are 7%, compared to about 20% for informal and subsistence workers. Even conditional on a separation, formal sector workers tend to stay more in their category and switch less to the other sector, than informal sector workers.

[43] The public release of the QLFS includes a household identifier which is consistent for repeated respondents. However, person identifiers within households may change if household composition has changed. I validate the person identifier by requiring consistency in gender, age, race, and educational attainment.

Table G1: **Frequency of worker transitions, by sector**

	Sector in t+1 (row %)						Col. prop.
	Formal	Informal	Subsist	Unemployed	NEA	Total	
Panel A: All workers							
Formal	91	4	1	3	2	100	34
Informal	18	65	3	10	4	100	9
Subsist	5	7	75	8	6	100	4
Unemployed	5	5	1	74	15	100	24
NEA	1	1	1	13	84	100	30
Panel B: Separations only							
Formal	25	5	1	46	23	100	49
Informal	6	22	1	52	19	100	37
Subsist	5	7	11	46	31	100	14

Notes. NEA indicates not economically active. Unemployed follows the expanded definition of unemployment, i.e. it includes those who would like a job but have not seeked employment in the last week. Subsist refers to informal single-worker business owners. The average separations proportion for formal, informal and subsist are (respectively) 7%, 20% and 18%.

Moreover, the wage changes across these transitions suggest that informal sector jobs pay lower than formal sector jobs for the same worker. Table G2 Panel B highlights gains of 2.5% for workers who switch across formal sector jobs (as shown in the main analysis), but large losses of -9.2% for workers who switch from formal to informal sector jobs. On the other hand, workers who switch from informal to formal sector jobs experience large wage gains of 11.2%. This asymmetry rules out that differences are mainly driven by, for example, wage losses on quitting. Rather, they imply that these formal sector jobs simply have higher wage premia.

Table G2: **Wage change over worker transitions, by sector**

	Formal	Informal	Average
Panel A: All workers			
Formal	1.2%	-3.1%	1.0%
Informal	3.4%	-0.4%	0.1%
Panel B: Separations only			
Formal	2.5%	-9.2%	1.1%
Informal	11.2%	1.4%	3.2%

Notes. NEA and unemployed are omitted as workers earn no wage in these categories. Subsist refers to informal single-worker business owners.

G.2 Informal sector firm labor supply elasticities

How does the existence of the informal sector affect the firm labor supply elasticities ε estimated in the main results? Firstly, one method of estimating the ε is to find the elasticity of *any* separation to the wage, regardless of destination. This means that the existence of the informal sector should not affect the main results, as long as they are considered as a firm labor supply elasticty for formal sector firms only.

Nonetheless, it is worth investigating the elasticity of formal job separations to informal jobs, as well as the elasticity of *informal* jobs to other states. Before discussing the results, note that the elasticities from these survey data are not comparable to the main results due to attenuation bias from error in measuring wages as well as fewer controls. The labor supply elasticities reported here are around 0.3 (with controls), which is far lower than the elasticities using the tax data of around 0.9 (or 1.6 using the movers specification). Of interest in this table are therefore the *relative* elasticities (assuming the bias is approximately constant across groups), and a similar approach is used in heterogeneity analysis in Langella and Manning (2021).

Controls do affect the relative estimates substantially (Table G3 columns 1-4). However, separations from a job in the formal sector to a job in the informal sector appear to be more sensitive to wages ($\varepsilon_{sep}^{F-I} = -0.27$) than separations to either formal sector jobs ($\varepsilon_{sep}^{F-F} = -0.17$) or unemployment ($\varepsilon_{sep}^{F-N} = -0.16$) (column 4). This could indicate informal firms poaching underpaid formal workers, or it could indicate that lower paid formal sector workers, after quitting, are more likely to have comparable informal jobs to work that are better than unemployment.

Workers employed in informal sector firms also appear to be sensitive to lower wages. The labor supply elasticity with controls of 0.3 is similar to that of formal sector workers for this dataset (column 6 compared to column 4). Recall that these are not subsistence single-worker business owners, but rather employees. They include, for example, domestic workers in private households, paid workers from informal sector enterprises, and informally employed workers in the formal sector. Perhaps informally employed workers may not face such different wage dynamics to their formal sector counterparts.

Table G3: **Firm labor supply elasticities, by sector**

	(1)	(2)	(3)	(4)	(5)	(6)
Separations to:						
Any job	-0.338	-0.164	-0.338	-0.164	-0.159	-0.151
	(0.013)	(0.015)	(0.013)	(0.015)	(0.012)	(0.014)
Formal job	-0.245	-0.167	-0.245	-0.167	-0.092	-0.157
	(0.030)	(0.034)	(0.030)	(0.034)	(0.055)	(0.062)
Informal or no job	-0.376	-0.169				
	(0.014)	(0.017)				
Informal job			-0.522	-0.273	-0.177	-0.167
			(0.048)	(0.056)	(0.027)	(0.030)
No job			-0.366	-0.162	-0.176	-0.163
			(0.015)	(0.018)	(0.015)	(0.017)
Labor supply elast.	0.676	0.328	0.676	0.328	0.318	0.302
	(0.052)	(0.060)	(0.052)	(0.060)	(0.048)	(0.056)
Obs (thousands)	79	79	79	79	31	31
Controls		Y		Y		Y
Current sector						
Formal	Y	Y	Y	Y		
Informal					Y	Y

Notes. The entries show separations elasticities where workers separate from a job in the "current sector" (last 2 rows) to a job (or no job) in the sector denoted in the estimate row heading. All separations refer to job separations, not sector. Coefficient rows indicating separate regressions pertaining to the sector of the new job (or no job). The labor supply elasticity is computed as -2 times the separations elasticity from the "any job" estimate. Controls refer to fixed effects for time, sex, years of education, race, and age.

G.3 Informal sector firm rent-sharing elasticities

As a last piece of insight into informal sector wage-setting, I investigate rent-sharing elasticities of informal sector firms. A cross-sectional firm-level survey is run every 4 years of informal businesses, by re-interviewing respondents in the QLFS who identified as informal business owners. Owners respond with information on sales, profits and employees. Most informal sector firms, 80%, are single-worker owner run businesses – termed survivalist or subsistence above, and these firms tend to have lower sales per worker.

Table G4: **Firm rent-sharing elasticities, informal firms**

	(1)	(2)	(3)	(4)	(5)	(6)
Rent share elast	0.324	0.259	0.406	0.351	0.447	0.350
	(0.038)	(0.035)	(0.033)	(0.037)	(0.038)	(0.040)
Obs	657	630	660	636	606	588
Rent measure	sales	sales	profit	profit	sales	sales
Includes owner					Y	Y
Controls		Y		Y		Y

Notes. Sales and profit are measures in log terms per worker. Rent share elasticity refers to the coefficient on the rent measure in a regression where the outcome is the establishment average wage (as in Equation 12). Controls include the industry, the number of employees by age, race and sex categories, as well as the owner's education.

Informal sector firms that employ workers appear to increase wages as sales or profits per worker increase. Table G4 report rent-sharing elasticities with controls in the range of 0.26 to 0.35. While fewer controls likely biases these estimates upwards, for example inadequate controls for worker quality, these magnitudes are high but in line with estimates for the formal sector. For example, my main results report a rent-sharing elasticity of 0.17 as the preferred estimate and 0.3 without worker quality controls using the tax data (see Table F1) – which is close to the range reported in Table G4. Including the owner salaries increases the rent-sharing estimates, suggesting that owners disproportionately increase their own salaries more (as would be expected in profit maximizing firms).

References

Abel, Martin, Rulof Burger, and Patrizio Piraino (2020). "The value of reference letters: Experimental Evidence from South Africa". In: *American Economic Journal: Applied Economics* 12.3, pp. 40–71.

Abowd, John M, Francis Kramarz, and David N Margolis (1999). "High wage workers and high wage firms". In: *Econometrica* 67.2, pp. 251–333.

Abowd, John M, Kevin L McKinney, and Ian M Schmutte (2019). "Modeling endogenous mobility in earnings determination". In: *Journal of Business & Economic Statistics* 37.3, pp. 405–418.

Aghion, Philippe, Eve Caroli, and Cecilia Garcia-Penalosa (1999). "Inequality and economic growth: the perspective of the new growth theories". In: *Journal of Economic literature* 37.4, pp. 1615–1660.

Alfaro, Laura, Andrew Charlton, and Fabio Kanczuk (2009). "Plant Size Distribution and Cross-Country Income Differences". In: *NBER international seminar on macroeconomics*. Vol. 5. 1. The University of Chicago Press Chicago, IL, pp. 243–272.

Alvarez, Jorge et al. (2018). "Firms and the decline in earnings inequality in brazil". In: *American Economic Journal: Macroeconomics* 10.1, pp. 149–89.

Ashenfelter, Orley C et al. (2022). "Monopsony in the Labor Market: New Empirical Results and New Public Policies". In: *Journal of Human Resources* 57.S, S11–S49.

Bachmann, Ronald, Gökay Demir, and Hanna Frings (2022). "Labor Market Polarization, Job Tasks, and Monopsony Power". In: *Journal of Human Resources* 57.S, S11–S49.

Bartelsman, Eric, John Haltiwanger, and Stefano Scarpetta (2013). "Cross-country differences in productivity: The role of allocation and selection". In: *American economic review* 103.1, pp. 305–34.

Bartelsman, Eric J and Zoltan Wolf (2017). "Measuring productivity dispersion". In.

Bassier, Ihsaan, Arindrajit Dube, and Suresh Naidu (2022). "Monopsony in Movers The Elasticity of Labor Supply to Firm Wage Policies". In: *Journal of Human Resources* 57.S, S50–s86.

Bassier, Ihsaan and Ingrid Woolard (2021). "Exclusive growth? Rapidly increasing top incomes amid low national growth in South Africa". In: *South African Journal of Economics* 89.2, pp. 246–273.

Bassier, Ihsaan et al. (2021). "Locked down and locked out: Repurposing social assistance as emergency relief to informal workers". In: *World Development* 139, p. 105271.

Basu, Kaushik (2003). *Analytical development economics: The less developed economy revisited*. MIT press.

Berger, David, Kyle Herkenhoff, and Simon Mongey (2022). "Labor market power". In: *American Economic Review* 112.4, pp. 1147–93.

Bloom, Nicholas and John Van Reenen (2010). "Why do management practices differ across firms and countries?" In: *Journal of economic perspectives* 24.1, pp. 203–24.

Bonhomme, Stéphane, Thibaut Lamadon, and Elena Manresa (2019). "A distributional framework for matched employer employee data". In: *Econometrica* 87.3, pp. 699–739.

Bonhomme, Stéphane et al. (2022). "How Much Should we Trust Estimates of Firm Effects and Worker Sorting?" In: *Journal of Labor Economics*.

Burdett, Kenneth and Dale T Mortensen (1998). "Wage differentials, employer size, and unemployment". In: *International Economic Review*, pp. 257–273.

Card, David (2022). "Who Set Your Wage?" In: *American Economic Review* 112.4, pp. 1075–90.

Card, David, Ana Rute Cardoso, and Patrick Kline (2016). "Bargaining, sorting, and the gender wage gap: Quantifying the impact of firms on the relative pay of women". In: *The Quarterly Journal of Economics* 131.2, pp. 633–686.

Card, David, Jörg Heining, and Patrick Kline (2013). "Workplace heterogeneity and the rise of West German wage inequality". In: *The Quarterly journal of economics* 128.3, pp. 967–1015.

Card, David et al. (2018). "Firms and labor market inequality: Evidence and some theory". In: *Journal of Labor Economics* 36.S1, S13–S70.

Cho, David (2018). *The labor market effects of demand shocks: Firm-level evidence from the recovery act*.

Chodorow-Reich, Gabriel (2020). "Regional data in macroeconomics: Some advice for practitioners". In: *Journal of Economic Dynamics and Control* 115, p. 103875.

Dal Bó, Ernesto, Frederico Finan, and Martín A Rossi (2013). "Strengthening state capabilities: The role of financial incentives in the call to public service". In: *The Quarterly Journal of Economics* 128.3, pp. 1169–1218.

Dickens, Richard, Stephen Machin, and Alan Manning (1999). "The effects of minimum wages on employment: Theory and evidence from Britain". In: *Journal of labor economics* 17.1, pp. 1–22.

Dodini, Samuel, Kjell G Salvanes, and Alexander Willén (2021). "The Dynamics of Power in Labor Markets: Monopolistic Unions versus Monopsonistic Employers". In: *Available at SSRN 3998033*.

Dube, Arindrajit, Laura Giuliano, and Jonathan Leonard (2019). "Fairness and frictions: The impact of unequal raises on quit behavior". In: *American Economic Review* 109.2, pp. 620–63.

Dube, Arindrajit, T William Lester, and Michael Reich (2016). "Minimum wage shocks, employment flows, and labor market frictions". In: *Journal of Labor Economics* 34.3, pp. 663–704.

Ebrahim, Amina, Murray Leibbrandt, and Vimal Ranchhod (2017). *The effects of the employment tax incentive on South African employment*. Tech. rep. WIDER Working Paper.

Fedderke, Johannes, Nonso Obikili, and Nicola Viegi (2018). "Markups and concentration in South African manufacturing sectors: an analysis with administrative data". In: *South African Journal of Economics* 86, pp. 120–140.

Fields, Gary S (2009). "Segmented labor market models in developing countries". In.

Finkelstein, Amy, Matthew Gentzkow, and Heidi Williams (2016). "Sources of geographic variation in health care: Evidence from patient migration". In: *The quarterly journal of economics* 131.4, pp. 1681–1726.

Garin, Andrew, Filipe Silvério, et al. (2019). *How responsive are wages to demand within the firm? evidence from idiosyncratic export demand shocks*. Tech. rep.

Gaure, Simen (2014). "Correlation bias correction in two-way fixed-effects linear regression". In: *Stat* 3.1, pp. 379–390.

Griliches, Zvi and Jerry A Hausman (1986). "Errors in variables in panel data". In: *Journal of econometrics* 31.1, pp. 93–118.

Hazell, Jonathon et al. (2021). *National wage setting*. Tech. rep. Working Paper.

Hirsch, Boris, Elke J Jahn, and Claus Schnabel (2018). "Do Employers Have More Monopsony Power in Slack Labor Markets?" In: *ILR Review* 71.3, pp. 676–704.

Hornstein, Andreas, Per Krusell, and Giovanni L Violante (2011). "Frictional wage dispersion in search models: A quantitative assessment". In: *American Economic Review* 101.7, pp. 2873–98.

Hsieh, Chang-Tai and Peter J Klenow (2009). "Misallocation and manufacturing TFP in China and India". In: *The Quarterly journal of economics* 124.4, pp. 1403–1448.

Hsieh, Chang-Tai and Benjamin A Olken (2014). "The missing" missing middle"". In: *Journal of Economic Perspectives* 28.3, pp. 89–108.

Hull, Peter (2018). *Estimating treatment effects in mover designs*. Tech. rep.

ILOstat (2021). *Statistics on the Informal economy*. URL: https://ilostat.ilo.org/topics/informality/ (visited on 10/27/2021).

Kerr, A and M Wittenberg (2017). "A Guide to Version 3.2 of the Post-Apartheid Labour Market Series (PALMS)". In: *DataFirst Portal, University of Cape Town*.

Kerr, Andrew (2018). "Job flows, worker flows and churning in south africa". In: *South African Journal of Economics* 86, pp. 141–166.

Kesar, Surbhi and Snehashish Bhattacharya (2020). "Dualism and structural transformation: The informal manufacturing sector in India". In: *The European Journal of Development Research* 32.3, pp. 560–586.

Kline, Patrick, Raffaele Saggio, and Mikkel Sølvsten (2020). "Leave-out estimation of variance components". In: *Econometrica* 88.5, pp. 1859–1898.

Kline, Patrick et al. (2019). "Who profits from patents? rent-sharing at innovative firms". In: *The Quarterly Journal of Economics* 134.3, pp. 1343–1404.

Kreuser, Carl Friedrich and Carol Newman (2018). “Total factor productivity in South African manufacturing firms”. In: *South African Journal of Economics* 86, pp. 40–78.

Lachowska, Marta et al. (2020). *Do Firm Effects Drift? Evidence from Washington Administrative Data*. Tech. rep. National Bureau of Economic Research.

Lamadon, Thibaut, Magne Mogstad, and Bradley Setzler (2022). “Imperfect competition, compensating differentials, and rent sharing in the US labor market”. In: *American Economic Review* 112.1, pp. 169–212.

Langella, Monica and Alan Manning (2021). “The measure of monopsony”. In: *Journal of the European Economic Association*.

Leibbrandt, Murray, Arden Finn, and Ingrid Woolard (2012). “Describing and decomposing post-apartheid income inequality in South Africa”. In: *Development Southern Africa* 29.1, pp. 19–34.

Leibbrandt, Murray, Vimal Ranchhod, and Pippa Green (2018). *Taking stock of South African income inequality*. Tech. rep. UNU-WIDER.

Lewis, W Arthur (1954). “Economic development with unlimited supplies of labour”. In: *The manchester school* 22.2, pp. 139–191.

Manning, Alan (2003a). *Monopsony in motion: Imperfect competition in labor markets*. Princeton: Princeton University Press.

— (2003b). “The real thin theory: monopsony in modern labour markets”. In: *Labour economics* 10.2, pp. 105–131.

— (2020). “Monopsony in labor markets: a review”. In: *ILR Review*.

McFadden, Daniel et al. (1973). “Conditional logit analysis of qualitative choice behavior”. In.

Meghir, Costas, Renata Narita, and Jean-Marc Robin (2015). “Wages and informality in developing countries”. In: *American Economic Review* 105.4, pp. 1509–46.

Mlatsheni, Cecil and Vimal Ranchhod (2017). “Youth labour market dynamics in South Africa: evidence from NIDS 1-2-3”. In: *SALDRU, University of Cape Town*.

Moore, Brendan and Judith Scott-Clayton (2019). *The Firm’s Role in Displaced Workers’ Earnings Losses*. Tech. rep. National Bureau of Economic Research.

Muralidharan, Karthik, Paul Niehaus, and Sandip Sukhtankar (2017). *General equilibrium effects of (improving) public employment programs: Experimental evidence from india*. Tech. rep. National Bureau of Economic Research.

Naidu, Suresh, Eric A Posner, and E Glen Weyl (2018). "Antitrust Remedies for Labor Market Power". In: *Harvard Law Review*.

National Treasury and UNU-WIDER (2020a). *CIT-IRP5 Firm Panel 2008-2018 [dataset]*. Version 4.0. Pretoria: South African Revenue Service [producer of the original data], 2019. Pretoria: National Treasury and UNU-WIDER [producer and distributor of the harmonized dataset], 2020.

— (2020b). *IRP5 2008-2018 [dataset]*. Version 4.0. Pretoria: South African Revenue Service [producer of the original data], 2019. Pretoria: National Treasury and UNU-WIDER [producer and distributor of the harmonized dataset], 2020.

Saez, Emmanuel, Benjamin Schoefer, and David Seim (2019). "Payroll taxes, firm behavior, and rent sharing: Evidence from a young workers' tax cut in Sweden". In: *American Economic Review* 109.5, pp. 1717–63.

Sokolova, Anna and Todd Sorensen (2021). "Monopsony in labor markets: A meta-analysis". In: *ILR Review* 74.1, pp. 27–55.

Song, Jae et al. (2018). "Firming up inequality". In: *The Quarterly Journal of Economics* 134.1, pp. 1–50.

Sorkin, Isaac (2018). "Ranking firms using revealed preference". In: *The quarterly journal of economics* 133.3, pp. 1331–1393.

Statistics South Africa (2010-2015). *Quarterly Labour Force Survey [dataset]*. URL: DOI : https://doi.org/10.25828/hhbh-tr16 (visited on 07/10/2019).

— (2011). *National Census [dataset]*.

Syverson, Chad (2011). "What determines productivity?" In: *Journal of Economic literature* 49.2, pp. 326–65.

Ulyssea, Gabriel (2018). "Firms, informality, and development: Theory and evidence from Brazil". In: *American Economic Review* 108.8, pp. 2015–47.

Webber, Douglas A (2016). “Firm-Level Monopsony and the Gender Pay Gap”. In: *Industrial Relations: A Journal of Economy and Society* 55.2, pp. 323–345.

— (2022). “Labor market competition and employment adjustment over the business cycle”. In: *Journal of Human Resources* 57.S, S87–S110.

World Bank (2020). *World Development Indicators*. URL: https://data.worldbank.org/indicator (visited on 09/22/2020).

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