Procompetitive Consequences of Workfare

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Abstract

Workfare programs—cash transfers conditioned on public-works labor—are usually justified on redistributive grounds. This paper asks whether they can also be justified as competition policy: by giving workers an outside option, workfare erodes employer market power. I combine evidence from a randomized workfare expansion in India (Muralidharan et al. (2023)) with new estimates of wage markdowns from the ICRISAT-VDSA survey to motivate and discipline a quantitative model of oligopsonistic competition with workfare (Berger et al. (2022)). Calibrated to key features of the setting, the model predicts that the procompetitive effects of workfare raise aggregate output 6% relative to a no-policy benchmark. The model implies that for every dollar of increased earnings due to the Indian workfare expansion, households gained an additional 34 cents due to the reduction in employer market power. Once the utility cost of workfare labor is taken into account, a constrained planner would choose a program as large as the one observed only if workfare were two and a half times as productive as the median private-sector firm. On their own, the procompetitive gains from workfare are therefore insufficient to rationalize the observed scale of the program.

Keywords: Oligopsonistic competition, efficiency, workfare programs.

JEL classifications: O11, J42, E24, J48.

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1 Introduction

Welfare policy in developing countries is commonly implemented through workfare programs (World Bank (2015), Besley and Coate (1992)). Workfare programs (also called employment guarantee programs) condition cash transfers on short-term, manual employment on public works. Beyond their redistributive role, workfare programs also create an outside option for workers and may therefore reduce employer market power. This paper focuses on workfare as a form of procompetitive policy.

I develop a quantitative model of oligopsonistic competition with endogenous wage markdowns, building on preference-based models of labor market power (Berger et al. (2022), Berger et al. (2025)). Workers' disutility from supplying labor involves imperfect substitution across firms, between workfare and private employment within a labor market, and across labor markets. Workfare, where the wage is exogenously set, draws workers away from private employers, flattening firms' residual labor supply curves and reducing wage markdowns. I characterize the effects of workfare on equilibrium private-sector wages and employment, and show how these effects depend on labor market concentration. Under parameterizations made precise in the analysis, the procompetitive effects of workfare can increase both private-sector wages and employment, with larger effects in more concentrated labor markets. These comparative statics motivate the calibration strategy and guide the interpretation of the quantitative results.

I discipline the model using evidence from a randomized expansion of India's workfare program in Andhra Pradesh (Muralidharan et al. (2023)). A reform that increased workfare participation also raised private-sector wages and private employment. The increase in private employment can be rationalized by the multiple treatments that the workfare expansion entails: increased cash transfers, the creation of productive public assets, and reduced employer market power. One of the findings of the workfare expansion experiment was that employment effects were larger in villages with more concentrated labor markets. The model delivers a theoretical mapping from labor market concentration to the size of the procompetitive effect, allowing this treatment-effect heterogeneity to identify the strength of the market power channel. I combine this moment with new evidence on wage markdowns in rural India to discipline the substitution elasticities governing employer market power. In particular, the aggregate wage markdown, the absence of a wage-size relationship, and the employment treatment gradient with respect to concentration jointly identify the elasticities that determine firms' labor supply curves.

The calibrated model implies substantial procompetitive effects of workfare on both private wages and employment. Roughly one sixth of the observed increase in private employment and one third of the increase in private wages generated by the workfare expansion can be attributed to reductions in employer market power. Put differently, for every dollar of additional household earnings generated due to the workfare expansion, households earned an additional 34 cents through higher private-sector earnings arising from reduced employer market power. The procompetitive effects of workfare raise aggregate output by 6% relative to a no-workfare benchmark. I use the calibrated model to study optimal policy. A planner who is constrained to implement equilibrium allocations can regulate the size of the workfare sector by choosing the workfare wage. Workfare reduces employer market power but diverts labor toward a public sector that is initially assumed to be unproductive. When distortions from employer market power are sufficiently severe, the planner optimally implements a positive level of workfare despite its lack of direct productive value. In the calibrated economy, however, the planner chooses not to operate workfare. I then allow workfare to produce output and ask what level of productivity would justify the observed scale of the program. The model implies that, if workfare uses the same production technology as private firms, it must be roughly two and a half times as productive as the median private firm to rationalize its observed scale.

Finally, I compare workfare with a more conventional labor market intervention, the minimum wage. An optimally chosen minimum wage dominates workfare as a procompetitive policy. However, when the minimum wage is not set optimally, a modestly productive workfare program can deliver larger welfare gains. This comparison is particularly relevant in environments where the level or enforcement of minimum wage regulations is imperfect.

The remainder of the paper proceeds as follows. Section 2 reviews the related literature. Section 3 presents evidence from the randomized experiment together with new evidence on wage markdowns from a survey of the rural agrarian economy in India. Section 4 develops the model and characterizes the effects of workfare on employer market power. Section 5 calibrates the model and quantifies the procompetitive multiplier. Section 6 studies optimal policy. Section 7 concludes. Proofs and additional derivations are collected in the appendix.

2 Literature

This paper contributes to the literature on labor market power. I use a preference-based quantitative model of market power (Atkeson and Burstein (2008), Edmond et al. (2015), Berger et al. (2022), Berger et al. (2025)) to study the labor market consequences of a policy that is widely used in developing countries: workfare (World Bank (2015),Besley and Coate (1992)).

A growing literature documents substantial employer market power in developing countries. Armangué-Jubert et al. (2025) and Brooks et al. (2021) estimate sizable wage markdowns among enterprises and formal and informal manufacturing. Sharma (2024) provides evidence of employer collusion in the textile industry in South India, while Felix (2026) documents labor market power among manufacturing firms in Brazil. Amodio et al. (2025) studies how self-employment shapes employer market power in Peru. I complement this literature by studying employer market power in a rural agrarian economy and by asking how workfare programs shape employer market power through their effect on workers' outside options.

The paper contributes to the largely empirical literature on workfare programs (Muralidharan et al. (2016), Imbert and Papp (2015), Imbert and Papp (2020), Klonner and Oldiges (2022)). Building on the experimental evidence in Muralidharan et al. (2023), I ask how much of the observed increase in private-sector employment and wages can be explained by reductions in employer market power. More broadly, the paper asks how far efficiency considerations alone can justify the scale of workfare programs. The paper is also related to the literature on quantifying equilibrium effects of policies in developing countries (Rotemberg (2019)).

Methodologically, the paper extends the quantitative framework of Berger et al. (2022) by introducing public employment as an additional outside option for workers. This extension yields new theoretical results on how public employment affects wage markdowns, aggregate employment and wages. Whereas Felix (2026) uses the framework to estimate labor supply elasticities, I exploit its general equilibrium structure to quantify the procompetitive effects of workfare and conduct policy counterfactuals. In discussing how workfare compares with the minimum wage as a labor market intervention, the paper suggests an alternative role for public employment (Berger et al. (2025)).

Finally, this paper speaks to the literature on labor markets in developing countries (Breza and Kaur (2025)) by combining insights from that literature with a structural model of labor market power. In doing so, it provides a structural evaluation of a randomized policy intervention in the spirit of Buera et al. (2020) and Kaboski and Townsend (2011).

3 Evidence

Fact 1: Workfare expansion in India increased wages and employment at privately owned firms.

Muralidharan et al. (2023) randomized a workfare expansion in the Indian state of Andhra Pradesh in 2011. In a random set of sub-districts, erstwhile cash disbursal of workfare payments was replaced with digital transfers. Digital payments reduced payment delays and leakages due to corruption, which were rampant under the cash disbursal regime. The reform had large effects on program access: workfare participation as measured by labor days spent in workfare went up by 30%[1]. The increased competition for labor drove reservation wages and realized private wages up: wages for labor went up by 10%. Interestingly, private employment (as measured by days spent in wage work) also went up, by 18%.

Muralidharan et al. (2023) find an earnings multiplier associated with the workfare expansion of about 7 - for every dollar of increased income due to the workfare expansion, total household income went up by 7 dollars[2]. The equilibrium effect of a workfare expansion on the economy works through a number of channels. Increased transfers through workfare have an associated fiscal multiplier. The best estimate of the fiscal multiplier in a comparable setting comes from Egger et al. (2022), who estimate it to be 2.5. While Egger et al. (2022)'s estimate comes from a transitory fiscal transfer, the Indian workfare program was widely expected to stay, and so the fiscal multiplier associated with the workfare expansion is likely higher. The workfare program also creates productive public assets such as roads, irrigation systems, etc. An increase in the marginal product of labor due to the public goods created by workfare could explain the joint increase in private employment and wages. However, reliable estimates of the productivity gains generated by workfare assets do not exist, and so it is not clear how important this channel might be.

Fact 2: Private employment effects of the workfare expansion were larger in villages with more concentrated landholdings.

Workfare has a potential procompetitive effect, which acts through the reduction in firm

[1]The baseline survey was conducted in June 2010, the improvement was implemented in June 2011 and the endline survey was conducted in June 2012. June is the agricultural lean season, and hence in this month the demand for workfare peaks. The experiment focussed on labor market outcomes in the month of June.

[2]Table 1 in Muralidharan et al. (2023) reports annual workfare earnings of households went up by Rs. 1295, while total earnings went up by Rs. 9579.

wage markdowns. Muralidharan et al. (2023) find that employment treatment effects of the workfare expansion are bigger in villages with a larger landholdings-based HHI. Muralidharan et al. (2023)'s setting is primarily agrarian; hence land-holdings concentration is plausibly correlated with labor market concentration. The treatment effect heterogeneity with respect to HHI is informative about the importance of the labor market power channel.

A structural model of labor market power would enable us to isolate the labor market power channel. How important might labor market power be in rural India? Existing estimates for wage markdowns in developing countries are only suggestive, since none of the estimates are specialised to a rural, primarily agrarian setting. Brooks et al. (2021) estimate wage markdowns between 30% to 70% of the worker's marginal product in Indian manufacturing, using data from the Annual Survey of Industries. Felix (2026) finds a wage markdown of 50% using data on formal sector workers and firms in Brazil. Armangué-Jubert et al. (2025) use formal sector data from the World Bank Enterprise Survey to estimate a wage markdown of 46% for Indian formal sector firms.

Fact 3: Wage markdowns are pervasive in rural India.

ICRISAT (Townsend (1994), Rosenzweig (2003)) maintains a plot-level panel running between 2009-2014 for 18 villages spread across south and central India, called Village Dynamics of South Asia (Foster and Rosenzweig (2022)). The VDSA includes rich data on the agricultural production process that enables backing out an estimate of the wage markdown. The strategy will follow two steps: under the assumption that farm production is Cobb-Douglas in labor hours, land and materials, I will estimate the elasticity of output to hours. Thereafter, this estimate is used to back out the wage markdown as the wedge between $MRPL$ and the wage per hour.

$Y_{i,t,s}$ is revenue on parcel i in year t and season s[3]. $L_{i,t,s}$ is the total labor hours including family labor hours. $T_{i,t,s}$ is the size of the cultivated parcel. $M_{i,t,s}$ is the total monetary value of materials, such as seed, pesticide, fertilizer, etc. Materials also include capital use such as tractor hours. When rented, machinery hours are valued at rent per hour. When owned, I impute the rent as the village-level median of rental prices for that machinery. $p(i)$ is the plot that the parcel belongs to. $\alpha_{p(i)}$ are features of the plot invariant over time. $\nu_{v(i),t,s,c(i,t,s)}$ is a fixed effect that captures specific features of village, year, season and 'main crop'; where main crop is the crop grown over the largest parcel on the plot in year t, season s. I estimate

[3] s is Kharif for summer crops and Rabi for winter crops.

a specification of the following form:

$$\log Y_{i,t,s} \;=\; \beta_L \log L_{i,t,s} + \beta_T \log T_{i,t,s} + \beta_M \log M_{i,t,s} + \alpha_p(i) + \nu_{v(i),t,s,c(i,t,s)} + \eta_{i,t,s} \qquad (1)$$

Identification exploits variation in log labor hours across parcels within a village $\times$ year $\times$ season $\times$ main-crop cell; the plot fixed effects $\alpha_{p(i)}$ absorb time-invariant differences in plot quality. (1) delivers $\widehat{\beta}_L = 0.49$.

Specification (1) is subject to an endogeneity concern; suppose the farmer observes a private signal $\omega_{i,t,s}$ that correlates positively with output and either positively or negatively with labor hours used. Importantly, suppose this signal is not absorbed by the rich structure of fixed effects included in (1). Following the control function approach of Levinsohn and Petrin (2003) delivers a bias-corrected estimate of β_L. Under the assumption that materials use is frictionless and monotonic in the signal, the signal is explicitly controlled for using a nonlinear function in materials (flexible in the signal) and plot size (predetermined with respect to the signal). A detailed explanation of the procedure is contained in the appendix. The estimate $\widehat{\beta}_L^{LP} = 0.403$ corrects the upward bias in the OLS (1).

Equipped with $\hat{\beta}_L^{LP}$ from the above regression, the wage markdown is backed out by constructing wage per hour and the $MRPL$. Wage per hour is constructed using detailed data on hired hours (harvesting, weeding, etc.) and activity-specific wage per hour. Let A be the set of activities.

$$wage_{i,t,s} = \frac{\sum_{a\in A} L^{hired}_{i,t,s,a} * wage\_per\_hour_{i,t,s,a}}{\sum_a L^{hired}_{i,t,s,a}}$$

$MRPL$ is constructed using data on total revenue at the parcel, season and year level, together with the total labor hours hired and the estimate of β_L.

$$MRPL_{i,t,s} = \beta_L \frac{revenue_{i,t,s}}{\sum_a L^{total}_{i,t,s,a}}$$

The markdown, then, is the wedge between the wage and $MRPL$.

$$\mu_{i,t,s} = \frac{wage_{i,t,s}}{MRPL_{i,t,s}}$$

Averaging markdowns on a plot across season-years and parcels, it is found that 11% have $\mu > 1$[4]. I attribute these to measurement error and retain the parcels for which $\mu \leq 1$ (Faia et al. (2026)). Figure 1 presents the distribution of plot-level wage markdowns. The left

[4] 18.5% of parcels across season years have a $\mu > 1$ prior to averaging. The average is parcel area weighted.

panel presents the distribution of markdowns conditional on $\mu < 1$, the right panel presents the unconditional distribution.

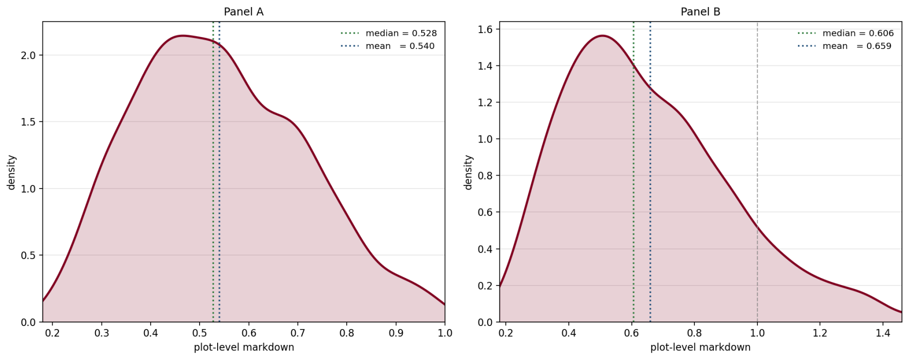

Figure 1: Plot-level markdown $\bar{\mu}_i$ = area-weighted mean of strip-level μ across the plot's (year, season, sub-parcel) cells. Strip-level μ is 5/95-trimmed throughout. Panel A applies an additional strip-level rule: strips with $\mu > 1$ are dropped *before* area-weighting, so $\bar{\mu}_i \leq 1$ by construction. This removes 86 plots (4.6% of the full sample) — those whose every strip had $\mu > 1$ — leaving n = 1,765. Panel B retains all strips; the full sample has n = 1,851 plots, of which 11.7% have $\bar{\mu}_i > 1$ (dashed line at $\mu = 1$). Green and blue dotted lines mark the median and mean.

Fact 4: Wage markdowns are bigger on larger plots.

I estimate the following specification that relates the wage markdowns calculated above to the size of the plot:

$$\log \mu_{p,t,s} \;=\; \gamma \cdot \log(\text{plot\_area}_{p,t,s}) \;+\; \nu_{v(p),t,s,c(p,t,s)} \;+\; \varepsilon_{i,t,s}$$

Here, plot level markdowns are an area-weighted average of parcel-level markdowns. Identifying variation is across-plot, within village, year, season and crop. Figure 2 shows that bigger plots have bigger wage markdowns. The elasticity of markdowns with respect to plot size is -0.15, statistically significant at 1%.

One concern might be that bigger parcels operate a technology with higher capital share. This might inflate $MRPL$ relative to the wage, because imposing a common production technology exaggerates the elasticity of output with respect to labor on larger plots. In the appendix, I show that materials as a share of revenue are not systematically different across plot sizes (Table 5).

Summary of Facts

A workfare expansion in India increased employment and wages at privately owned firms (Fact 1). The measured treatment effect of the workfare expansion bundles together a number of channels. The heterogenous treatment effect in more concentrated labor markets (Fact 2) suggests a role for the procompetitive channel. Fact 3 establishes that a rural agrarian economy surveyed in ICRISAT-VDSA, similar to Muralidharan et al. (2023)'s setting, features pervasive wage markdowns. Fact 4 establishes that bigger plots implement larger wage markdowns. Fact 3 and 4 by themselves are not evidence of labor market power - they could be rationalized, for instance, in a model of size dependent frictions (Hsieh and Klenow (2009)). I interpret the evidence on wage markdowns through the lens of a model of market power, that enables us to speak to Facts 1 and 2. The model endogenously generates the documented relationship between size and market power (Atkeson and Burstein (2008), Edmond et al. (2015), Berger et al. (2022), Berger et al. (2025)). Disciplining the model to quantitatively match Fact 2 (bigger treatment effects in more concentrated markets) enables us to back out the contribution of labor market power channel to the aggregate employment and wage effects documented in Fact 1.

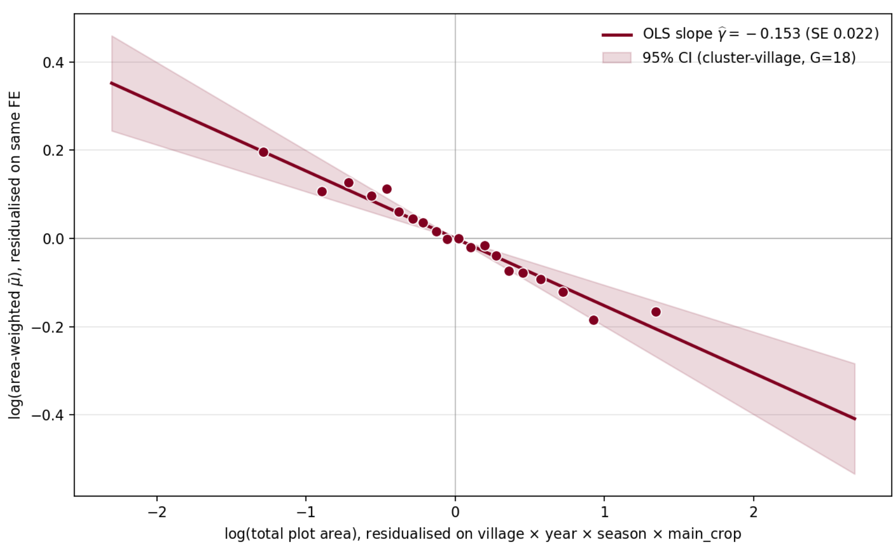

Figure 2: Residualised binscatter of $\log \mu$ on log(plot_area) partialling out village $\times$ year $\times$ season $\times$ main-crop fixed effects. 20 equal-frequency bins; shaded band is the 95% CI under village-level clustering ($G = 18$). $\widehat{\gamma} = -0.15$ (SE 0.022), $n = 7{,}980$.

4 Model

I develop a model of oligopsonistic competition with endogenously variable wage markdowns that features a positive relationship between firm size and the wage markdown. The model consists of a continuum of local labor markets with a finite number of firms and a workfare option in each labor market (Berger et al. (2022), Berger et al. (2025)). A representative household allocates ex-ante identical workers across firms and workfare in each market. Workers draw logit preference shocks at three levels: the market, workfare versus the private economy, and firms within the private economy. As a firm becomes bigger, the labor supply facing it becomes steeper; generating a positive covariance between size and markdown. Workfare takes away a share of the local labor market, flattening the labor supply curve facing firms and reducing wage markdowns. Effects are biggest at the largest firms that directly compete with workfare for labor.

4.1 Environment

The economy consists of $j \in [0, 1]$ labor markets; within each labor market there is a market ('private') sector and a workfare option. The market sector consists of m_j firms heterogenous in productivity. The workfare sector consists of a workfare project with exogenously given wage $\bar{w}_j$.

4.1.1 Household

A representative household allocates measure n_{ij} workers to firm i in labor market j and a measure $\{n_j^w\}$ workers to the workfare program in labor market j. The disutility from labor is three-nested CES; with the microfoundation of three-level logit shocks. The consumption good c_{ij} is perfectly substitutable across firms and is numeraire. The household is one-period lived, and its earnings consist of labor earnings from the private market for labor, the workfare sector and profits subject to a tax τ used to finance the workfare program.

$$
\begin{aligned}
&\max_{\{c_{ij}, n_{ij}, n_j^w\}} \; U(C, N) \\
&\text{s.t.} \quad C = \int_0^1 \left(\sum_i w_{ij} n_{ij} + \bar{w}_j n_j^w \right) dj + (1-\tau)\Pi \\
&\text{where} \quad C = \int_0^1 \sum_i c_{ij} dj \qquad n_j^p = \left(\sum_{i=1}^{m_j} (n_{ij})^{\frac{\eta+1}{\eta}} \right)^{\frac{\eta}{\eta+1}} \\
&\text{and} \quad n_j = \left((n_j^p)^{\frac{\gamma+1}{\gamma}} + (n_j^w)^{\frac{\gamma+1}{\gamma}} \right)^{\frac{\gamma}{\gamma+1}} \qquad N = \left(\int_0^1 n_j^{\frac{\theta+1}{\theta}} \, dj \right)^{\frac{\theta}{\theta+1}}
\end{aligned}
$$

The CES structure of the model allocates N across labor markets, across private and workfare sectors within each labor market and across firms within the private sector. An increase in N is thought of as drawing workers into the labor market, from unemployment, unpaid work at home and self-employment[5]. In Muralidharan et al. (2023)'s baseline survey, the typical household works in the labor market (private and workfare) for half a month, hence any constraint on N is non-binding. For workfare to affect firm wage markdowns, firms need to be granular in local labor markets – this motivates a model of oligopsonistic competition.

4.1.2 Firms

To become big, a firm must draw workers farther in preference space. This delivers an upward sloping labor supply curve, which the firm internalises when it solves its profit maximization problem. The firm hires too little relative to the competitive benchmark due to the externality imposed by the marginal worker on the wage paid by the firm to all its workers. The household's first order condition implies the labor supply curve facing firm i in village j:

$$
w_{ij} = \left(\frac{n_{ij}}{n_j^p} \right)^{\frac{1}{\eta}} \left(\frac{n_j^p}{n_j} \right)^{\frac{1}{\gamma}} \left(\frac{n_j}{N} \right)^{\frac{1}{\theta}} W \tag{2}
$$

where the following are true by definition

$$
w_j^p n_j^p = \sum_{i=1}^{m_j} w_{ij} n_{ij} \quad w_j n_j = w_j^p n_j^p + \bar{w}_j n_j^w \quad WN = \int_0^1 w_j n_j \, dj
$$

[5] Donovan et al. (2023) argue that self-employment and unemployment are comparable states in developing countries. Amodio et al. (2025) study how self-employment shapes the labor market power of firms in Peru - that is not the focus of this paper.

which, given the CES structure imply wage indices:

$$w_j^p = \left(\sum_i^{m_j} w_{ij}^{1+\eta} \right)^{\frac{1}{1+\eta}} \qquad w_j = \left((w_j^p)^{1+\gamma} + \bar{w}_j^{1+\gamma} \right)^{\frac{1}{1+\gamma}} \qquad W = \left(\int_0^1 w_j^{1+\theta} dj \right)^{\frac{1}{1+\theta}}$$

Firms draw idiosyncratic productivity z_{ij} and operate a decreasing returns to scale technology. The firm's problem is given by:

$$\max_{n_{ij}} \left\{ z_{ij} n_{ij}^{\alpha} - w_{ij} \left(n_{ij}, n_j^p, n_j^w, N, W \right) n_{ij} \right\}$$

$$\text{subject to} \quad w_{ij} \left(n_{ij}, n_j^p, n_j^w, N, W \right) = \left(\frac{n_{ij}}{n_j^p} \right)^{\frac{1}{\eta}} \left(\frac{n_j^p}{n_j} \right)^{\frac{1}{\gamma}} \left(\frac{n_j}{N} \right)^{\frac{1}{\theta}} W$$

Note that the firm is restricted to linear pricing (Bornstein and Peter (2025)). The assumption is supported by evidence on common village-level wages in developing countries (Breza and Kaur (2025)). Common village-level wages also imply that wage dispersion across firms is eliminated; the quantitative model will utilize this evidence as a calibration target. The firm's first order condition delivers the usual Lerner index:

$$\alpha \frac{y_{ij}}{n_{ij}} = w_{ij} + \frac{\partial w_{ij}}{\partial n_{ij}} n_{ij}$$

Define $\varepsilon_{ij} := \left[\frac{\partial log w_{ij}}{\partial log n_{ij}} \right]^{-1}$. Then,

$$w_{ij} = \mu_{ij} \alpha \frac{y_{ij}}{n_{ij}}, \quad \mu_{ij} = \frac{\varepsilon_{ij}}{1 + \varepsilon_{ij}} \tag{3}$$

4.1.3 Workfare

Workfare is an outside option in each labor market. Workfare has no objective - workers see the exogenous workfare wage and get allocated away from firms. Workfare, thus, affects the equilibrium by taking away a share of the local labor market. The idea is to ask; how far can we go making a case for workfare which is purely grounded in efficiency? In the quantitative exercise, workfare is a productive economic activity; the model can be used to back out the size of workfare productivity that justifies any given workfare scale. The model abstracts from any redistributive role for workfare. The exercise is in the spirit of Berger et al. (2025) who separate the redistributive role of minimum wages from efficiency gains.

4.1.4 Equilibrium

Given $\{\bar{w}_j\}$, an equilibrium consists of $\left\{ w_{ij}, n_{ij}, n_j^w \right\}_{\forall i,j}$, household consumption C, output Y, government spending G and a tax rate τ such that

1. each $\left\{w_{ij}, n_{ij}, n_j^w\right\}$ consistent with the household's labor supply curve

2. each n_{ij} solves the firm's problem

3. the government's budget is balanced

$$\int_0^1 \bar{w}_j n_j^w = \tau \Pi$$

4. the goods market clears

$$C = Y$$

4.2 Results

I make a simplifying assumption to convey the main intuition and derive aggregation results. This assumption makes the workfare wage endogenous; the workfare wage is assumed to be a constant fraction ϕ of the equilibrium private wage in the local labor market. This assumption is relaxed in the quantitative analysis of the model.

Assumption 1. $\bar{w}_j = \phi w_j^p$

Define s_{ij} to be the payroll of a firm as a fraction of the total private payroll in its labor market. The payroll share is given by:

$$s_{ij} = \frac{n_{ij} w_{ij}}{\sum_i^{m_j} n_{ij} w_{ij}}$$

4.2.1 Market and general equilibrium

Result 1. *(Within-market equilibrium) Under assumption 1, markdowns in market j, $\{\mu_{ij}\}_{i=1}^{m_j}$, can be recovered without knowing aggregates:*

$$\begin{aligned} s_{ij} &= \frac{\left[\mu(s_{ij}) z_{ij}\right]^{\frac{\eta+1}{1+\eta(1-\alpha)}}}{\sum_i^{m_j} \left[\mu(s_{ij}) z_{ij}\right]^{\frac{\eta+1}{1+\eta(1-\alpha)}}} \\ \mu(s_{ij}) &= \frac{\varepsilon(s_{ij})}{\varepsilon(s_{ij}) + 1} \\ \varepsilon(s_{ij}) &= \left((1 - s_{ij})\frac{1}{\eta} + s_{ij}(1 - \Phi^{-(1+\gamma)})\frac{1}{\gamma} + s_{ij}\Phi^{-(1+\gamma)}\frac{1}{\theta}\right)^{-1} \end{aligned}$$

where

$$\Phi = \left(1 + \phi^{\gamma+1}\right)^{\frac{1}{1+\gamma}}$$

where Φ is an index of workfare performance, and $\Phi^{-\gamma}$ is the private market share of the village. The elasticity of labor supply is a share-weighted harmonic average of the three substitution elasticities.

Observe that the first order effect of a workfare expansion (holding s constant) is to flatten the elasticity of labor supply facing the firm, provided $\gamma > \theta$. Workfare improvements create a local outside option for workers provided it is easier for them to substitute away to workfare than to leave the local labor market. Thus, when substituting away to workfare is easy enough, workfare improvements narrow the wage markdown by increasing local competition.

One feature of the model under assumption 1 is block recursivity; equilibrium distribution of wage markdowns can be solved independent of aggregates. Hence, the market equilibrium is separable from the general equilibrium. Without assumption 1, the model no longer admits this separability.

I define the aggregate private employment index. This index aggregates over the private labor across labor markets.

$$N^p = \left(\int_0^1 \left(n_j^p \right)^{\frac{\theta+1}{\theta}} \right)^{\frac{\theta}{\theta+1}}$$

Under Assumption 1, there exists a number W^p, such that

$$W^p N^p = \int_0^1 w_j^p n_j^p dj$$

and W^p has the expected form,

$$W^p = \left(\int_0^1 \left(w_j^p \right)^{1+\theta} \right)^{\frac{1}{1+\theta}}$$

Given equilibrium markdowns in the continuum of villages and firm productivities, aggregates are recovered as the solution to a system of equations.

Result 2. *(Aggregation) Under assumption 1, the following system pins down* $\{Y, C, W^p, N^p, W, N\}$.

$$Y = \Omega \tilde{Z} \left(N^p \right)^{\alpha} \qquad W^p = \alpha \frac{\mu}{\Omega} \frac{Y}{N^p} \qquad W = \frac{-U_N}{U_C} \tag{4}$$

$$W = \Phi W^p \qquad N = \Phi^{\gamma} N^p \qquad C = Y \tag{5}$$

where the constants Z, Ω and μ are;

$$Z = \left[\int_0^1 z_j^{\frac{1+\theta}{1+\theta(1-\alpha)}} dj\right]^{\frac{1+\theta(1-\alpha)}{1+\theta}} \quad , \quad z_j = \left[\sum_{i=1}^{m_j} z_{ij}^{\frac{1+\eta}{1+\eta(1-\alpha)}}\right]^{\frac{1+\eta(1-\alpha)}{1+\eta}}$$

$$\mu = \left[\int_0^1 \left(\frac{z_j}{Z}\right)^{\frac{1+\theta}{1+\theta(1-\alpha)}} \mu_j^{\frac{1+\theta}{1+\theta(1-\alpha)}} dj\right]^{\frac{1+\theta(1-\alpha)}{1+\theta}} \quad , \quad \mu_j = \left[\sum_{i=1}^{m_j} \left(\frac{z_{ij}}{z_j}\right)^{\frac{1+\eta}{1+\eta(1-\alpha)}} \mu_{ij}^{\frac{1+\eta}{1+\eta(1-\alpha)}}\right]^{\frac{1+\eta(1-\alpha)}{1+\eta}}$$

$$\Omega = \int_0^1 \left(\frac{z_j}{Z}\right)^{\frac{1+\theta}{1+\theta(1-\alpha)}} \left(\frac{\mu_j}{\mu}\right)^{\frac{\alpha\theta}{1+\theta(1-\alpha)}} \omega_j dj, \quad \omega_j = \sum_{i=1}^{m_j} \left(\frac{z_{ij}}{z_j}\right)^{\frac{1+\eta}{1+\eta(1-\alpha)}} \left(\frac{\mu_{ij}}{\mu_j}\right)^{\frac{\eta\alpha}{1+\eta(1-\alpha)}}$$

In (4), the first equation is an aggregate production function, the second is the 'representative' firm's labor first order condition and the third equation is the representative household's labor first order condition. In (5), the first two equations represent the aggregate wage and labor indices W and N in terms of the aggregate private wage and labor indices W^p and N^p. The third equation in (5) is the goods market clearing condition. $\tilde{Z}$, Ω and μ are respectively indices of aggregate productivity, a misallocation wedge that comes from the covariance between markdowns and productivity and an aggregate markdown that occurs due to market power. In Berger et al. (2022) $W = W^p$ and $N = N^p$ so that (4) and (5) reduce to four equations in four unknowns.

4.2.2 Employment and wages

I study the observable implications of workfare expansion for private employment and wages. The results derived here build directly on Result 2. To throw light on main mechanisms, this section presents analytical expressions under the assumption of firm homogeniety. This assumption enables getting rid of endogenous shares, and the misallocation wedge. Firm heterogeneity is reintroduced in quantitative exercises. Household preferences are parameterized to be CRRA, with $\frac{1}{\nu}$ the Frisch elasticity of labor supply.

$$U(C,N) = \frac{C^{1-\sigma}}{1-\sigma} - \frac{N^{1+\nu}}{1+\nu} \tag{6}$$

Let equilibrium firm-level output be y, employment n, wage w, markdown μ. Markdowns have the following expression:

$$\mu = \frac{1}{1+\varepsilon^{-1}} \qquad \varepsilon^{-1} = \left(\frac{m-1}{m}\frac{1}{\eta} + \frac{1}{m}\frac{1}{\gamma} + \frac{1}{m}\Phi^{-(1+\gamma)}\left(\frac{1}{\theta} - \frac{1}{\gamma}\right)\right)$$

When $\gamma > \theta$, $\frac{dlog\mu}{dlog\Phi} > 0$ (all proofs in appendix).

Result 3. *(Employment and wage responses) Under assumption 1 and homogeneous firms,*

$$\frac{d\log n}{d\log\Phi} = (1-\gamma\nu)\frac{1}{\alpha(\sigma-1)+\nu+1} + \frac{1}{\alpha(\sigma-1)+\nu+1}\frac{dlog\mu}{dlog\Phi}$$
$$\frac{d\log w}{d\log\Phi} = (\gamma\nu-1)\frac{1-\alpha}{\alpha(\sigma-1)+\nu+1} + \frac{\alpha\sigma+\nu}{\alpha(\sigma-1)+\nu+1}\frac{dlog\mu}{dlog\Phi}$$

When workfare improves, labor supply facing the firm shifts and tilts. The first component in the derivatives captures the shift in the labor supply curve facing firms. The direction of the shift depends on how the substitutability between workfare and private jobs (γ) compares with the Frisch elasticity of labor supply ($\frac{1}{\nu}$). When $\gamma > \frac{1}{\nu}$, workfare expansion reallocates labor away from firms, so the labor supply facing firms shifts left. This has a negative effect on firm employment and a positive effect on firm wage. When $\gamma < \frac{1}{\nu}$, there is a scale effect: an increase in the aggregate wage index (CES aggregate of private and workfare wages) draws more people out of non-market activities (no work or work not accounted for in the model, such as self-production) into the labor market. The scale effect shifts labor supply facing the firm to the right. This has a positive effect on employment and a negative effect on the wage. The second term in the derivatives captures the efficiency consequences of workfare expansion: the labor supply curve facing the firm becomes flatter, provided $\gamma > \theta$. The efficiency improvement due to workfare expansion has positive effects on wages and employment ($\frac{dlog\mu}{dlog\Phi} > 0$). Workfare expansion drives an increase in private employment and wages in the model under the following parametric condition.

Corollary 1. *Firm employment and wages increase when workfare expands provided*

$$1 - \frac{\alpha\sigma+\nu}{1-\alpha}\frac{d\log\mu}{d\log\Phi} \;<\; \gamma\nu \;<\; 1 + \frac{d\log\mu}{d\log\Phi}$$

Corollary 1 tells us that workfare programs could have the same observable implications as an appropriately set minimum wage. Note that this is true although no firms are constrained: minimum wages work by constraining firms that pay low wages, while workfare programs work by increasing competition for workers. This is especially important for settings with weak enforcement of minimum wage laws; we offer a more extensive discussion of workfare as a labor market intervention in section 6.3.

4.2.3 Firm heterogeneity

Workfare wage is exogenous $\bar{w}_j = \bar{w}$, and firm productivities are drawn from a Pareto distribution.

Result 4. *(Within-market markdowns) Markdowns in market j, $\{\mu_{ij}\}_{i=1}^{m_j}$ are a solution to the following system:*

$$s_{ij} = \frac{[\mu(s_{ij})z_{ij}]^{\frac{\eta+1}{1+\eta(1-\alpha)}}}{\sum_i^{m_j}[\mu(s_{ij})z_{ij}]^{\frac{\eta+1}{1+\eta(1-\alpha)}}} \tag{7}$$

$$\mu(s_{ij}) = \frac{\varepsilon(s_{ij})}{\varepsilon(s_{ij})+1} \tag{8}$$

$$\varepsilon(s_{ij}) = \left((1-s_{ij})\frac{1}{\eta} + s_{ij}\left(1-\left(\frac{n_j^p}{n_j}\right)^{\frac{\gamma+1}{\gamma}}\right)\frac{1}{\gamma} + s_{ij}\left(\frac{n_j^p}{n_j}\right)^{\frac{\gamma+1}{\gamma}}\frac{1}{\theta}\right)^{-1} \tag{9}$$

Markdowns are a solution to a set of equations that is a fixed point in shares s_{ij} given the object $\frac{n_j^p}{n_j}$. Private relative to market-level labor is endogenous and dependent on aggregates, and hence, the market equilibrium cannot be solved independent of aggregates. To compute the equilibrium, we guess the market-specific endogenous wedge $\phi_j = \frac{\bar{w}_j}{w_j^p}$ and then iterate on the guess using the structure of the model (computation algorithm detailed in appendix).

Figure 3 illustrates procompetitive effects of workfare in the model with firm heterogeneity. Consider identical labor markets, each labor market consisting of $m = 9$ firms with productivity fixed at 10th, 20th...90th percentiles of the Pareto distribution. The 'post' economy is solved with a 30% higher workfare wage relative to the 'pre' economy. Firm heterogeniety reveals another feature of the procompetitive effects of workfare; effects are larger at firms with a larger initial market share. From (9), it is apparent that workfare improvements are less consequential as $s \to 0$. A small firm primarily competes with other firms within its local labor market for the household's private sector labor allocation. When a firm is big, it is primarily competing against workfare and other labor markets. Thus, the local outside option created by workfare generates bigger efficiency improvements at locally big firms. Note that the illustrated workfare expansion reallocates market shares (within the set of firms) towards more productive firms, and at the same time reduces the aggregate inefficiency due to wage markdowns[6].

The intuition illustrated in Figure 3 is formalized in the following proposition. Let $\phi_j = \frac{\bar{w}}{w_j^p}$. Then,

[6]Note that theory predicts that workfare expansions should have no effect on markdowns when $s \to 0$. In typical calibrations with $m = 10$ firms, this limit is never achieved in equilibrium, and thus, we do observe effects on markdowns even at the smallest firms.

Result 5. *(Firm-level markdown response) Holding shares fixed,*

$$\left.\frac{d\log\mu_{ij}}{d\log\phi_j}\right|_s = \mu_{ij}\cdot s_{ij}\cdot(1+\gamma)\left(\frac{n_j^p}{n_j}\right)^{\frac{\gamma+1}{\gamma}}\left(1-\left(\frac{n_j^p}{n_j}\right)^{\frac{\gamma+1}{\gamma}}\right)\cdot\left(\frac{1}{\theta}-\frac{1}{\gamma}\right) \tag{10}$$

$$= \mu_{ij}\cdot s_{ij}\cdot(1+\gamma)\frac{\phi_j^{1+\gamma}}{\left(1+\phi_j^{1+\gamma}\right)^2}\cdot\left(\frac{1}{\theta}-\frac{1}{\gamma}\right) \tag{11}$$

To a first order (holding shares fixed), the effect of workfare expansion on a firm's wage markdown acts through the forces presented in (10); $\left(\frac{n_j^p}{n_j}\right)^{\frac{\gamma+1}{\gamma}}\left(1-\left(\frac{n_j^p}{n_j}\right)^{\frac{\gamma+1}{\gamma}}\right)$ is the rate of reallocation of mass inside the inverse elasticity expression from the inelastic across-markets margin to the more elastic workfare margin. The payoff per unit of mass moved is the gap $\left(\frac{1}{\theta}-\frac{1}{\gamma}\right)$, which captures the strength of the local outside option created by workfare. This response is scaled by the exposure of the firm s_{ij}, which is its local payroll share, and is dampened by μ_{ij}, since the markdown is concave in the inverse elasticity, so that when the inverse elasticity is high (i.e μ is small), the passthrough to the markdown is dampened. Under assumption 1, $\phi_j = \phi$ is a constant; so the size of efficiency gains at big versus small firms depends only on whether the exposure channel s_{ij} dominates the dampening channel μ_{ij}, since s_{ij} and μ_{ij} covary negatively.

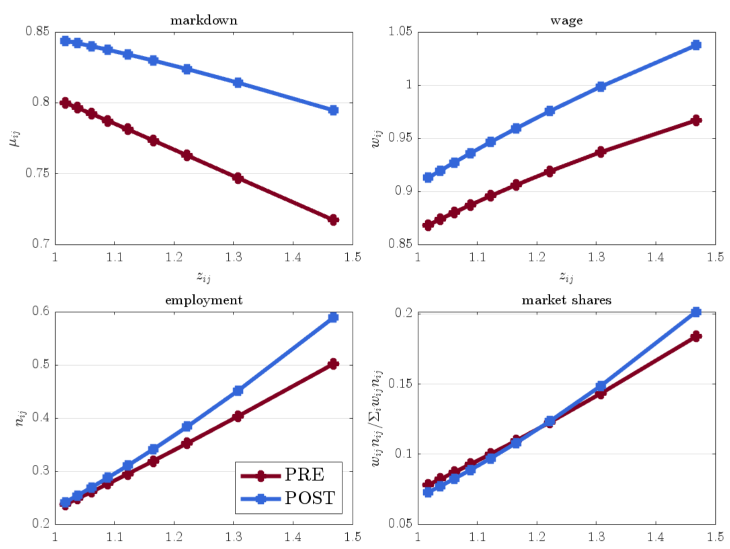

Figure 3: The simulation borrows from Berger et al. (2022)'s calibration for the US and sets $\theta = 0.45$, $\eta = 6.96$, $\alpha = 0.8$. We set $\xi = 6$ (Pareto tail), $\nu = 0.2$. Preferences are GHH. The baseline workfare wage is set to match a workfare-private labor allocation of 0.57, consistent with the empirical setting in India. The 'post' economy features a 30% higher workfare wage relative to the 'pre' economy.

4.2.4 Workfare in more concentrated markets

The following result characterises the link between labor market concentration and the size of efficiency gains.

Result 6. *(Market-level markdown response and concentration) Define a markdown-damped HHI as* $\tilde{H}_j = \sum_i^{m_j} s_{ij}^2 \mu_{ij}$. *Holding shares fixed,*

$$\left.\frac{dlog\mu_j}{dlog\phi_j}\right|_s = (1+\gamma)\left(\frac{n_j^p}{n_j}\right)^{\frac{\gamma+1}{\gamma}}\left(1-\left(\frac{n_j^p}{n_j}\right)^{\frac{\gamma+1}{\gamma}}\right)\left(\frac{1}{\theta}-\frac{1}{\gamma}\right)\tilde{H}_j \tag{12}$$

$$= (1+\gamma)\frac{\phi_j^{1+\gamma}}{\left(1+\phi_j^{1+\gamma}\right)^2}\left(\frac{1}{\theta}-\frac{1}{\gamma}\right)\tilde{H}_j \tag{13}$$

The market-level efficiency gain is proportional to the markdown-damped HHI. Under assumption 1, $\phi_j = \phi$ and the size of the efficiency gain at the market-level is unambiguously increasing in the markdown-damped HHI. The following result characterises how efficiency gains pass through to employment.

Result 7. *(Market-level employment response and concentration) Define a markdown-damped HHI as* $\tilde{H}_j = \sum_i^{m_j} s_{ij}^2 \mu_{ij}$. *Holding shares fixed,*

$$dlogn_j^p = a_j + b_j\tilde{H}_j \tag{14}$$

where

$$a_j = \frac{(\theta-\gamma)(1-\left(\frac{1}{1+\phi_j^{1+\gamma}}\right))}{1+\theta(1-\alpha)}dlog\phi_j \qquad b_j = \frac{\theta(1+\gamma)\frac{\phi_j^{1+\gamma}}{\left(1+\phi_j^{1+\gamma}\right)^2}\left(\frac{1}{\theta}-\frac{1}{\gamma}\right)}{1+\theta(1-\alpha)}dlog\phi_j \tag{15}$$

Under assumption 1, $\phi_j = \phi$ and hence $a_j = a_k = a, b_j = b_k = b$, the difference in employment effects across labor markets with different level of concentration can be characterised as:

$$dlogn_j^p - dlogn_k^p = b\left(\tilde{H}_j - \tilde{H}_k\right) \tag{16}$$

Thus, more concentrated labor markets feature bigger private employment effects of the workfare expansion. The size of the difference is regulated by b. Note that in the competitive limit, $\tilde{H} \to 0$, and the local effect of a workfare expansion (holding aggregate N fixed) on private employment is unambiguously negative. A workfare improvement implemented in the entire economy (ϕ_j goes up in all j) would elicit an adjustment in N, and whether aggregate private employment goes up or down in the competitive limit depends on whether the extensive margin compensates for the reallocation of labor from private firms to workfare (as discussed in the previous subsection). Since the adjustment to aggregate N and W is identical across labor markets, the expression (16) is always true under assumption 1.

b summarizes the effect of concentration on the size of employment gains. Given θ, α and the workfare wage ϕ, γ pins down b.

In the quantitative model with a fixed wage $\bar{w}$, the wedges ϕ_j are heterogeneous. This introduces other channels that mediate the sign of the employment effect with respect to $\tilde{H}$:

$$dlogn_j^p - dlogn_k^p = (a_j - a_k) + b_j\tilde{H}_j - b_k\tilde{H}_k \tag{17}$$

All these forces could either amplify or attenuate the cross-$\tilde{H}$ effects, depending, in part, on whether wages are higher or lower in more concentrated markets (i.e. whether ϕ_j increases or decreases in concentration)[7]. Given other parameters, γ pins down the equilibrium objects $\{a_j, b_j\}$ that determine the cross-concentration employment treatment effect.

Muralidharan et al. (2023) presents evidence that employment effects of the workfare expansion were larger in villages with more concentrated labor markets. Their measure of labor market concentration is a village-level HHI calculated using household landholdings from survey data. While in the data s_{ij} are landholdings shares, in the model s_{ij} are payroll shares. I discipline the model to match the coefficient $\beta_{T\times HHI}$ (scaled to baseline private employment) from the following regression:

$$emp_j \;=\; cons \;+\; \beta_T T_j \;+\; \beta_{HHI} HHI_j \;+\; \beta_{T\times HHI} T_j * HHI_j \;+\; \varepsilon_j \tag{18}$$

Note that analytical results give us the model-implied link between employment effects and the markdown-damped HHI. Since the empirical exercise uses HHIs (and the kind of data needed to construct markdown-damped HHIs in Muralidharan et al. (2023)'s experimental setting are not available), the calibration uses the HHI as a measure of concentration. Suppose the operator $\mathbb{E}_j^w$ calculates a payroll-share weighted average

$$HHI_j = \mathbb{E}_j^w(s) \qquad \tilde{H}_j = \mathbb{E}_j^w(s\mu) \qquad \tilde{H}_j = HHI_j \cdot \mathbb{E}^w(\mu) + cov^w(s,\mu) \tag{19}$$

The cross-HHI employment treatment effect additionally depends on the cross-market dispersion in average markdown and the cross-market dispersion in covariance between markdowns and shares.

[7] More concentrated markets feature higher market-level markdowns, but also higher market-level productivity. Hence markets with different $\tilde{H}$ cannot be unambiguously ranked on employment and wages.

5 How big were procompetitive effects of workfare?

To quantify the procompetitive consequences of workfare, I specialize the model above to the setting studied in Muralidharan et al. (2023). A workfare expansion of the same size as in the empirical experiment is implemented in the model. I treat the employment treatment gradient in HHI as the key moment that identifies the market power channel. Thus, the model is disciplined to reproduce the employment treatment gradient in HHI, and model-predicted aggregate employment and wage effects are interpreted as the procompetitive consequences of the workfare expansion.

The key parameters to be disciplined are the CES elasticities $\{\eta, \gamma, \theta\}$. Three empirical moments identify these elasticities: (i) the absence of a wage-size relationship in the ICRISAT-VDSA, (ii) the employment treatment gradient with respect to labor market concentration documented by Muralidharan et al. (2023), and (iii) the aggregate wage markdown estimated from the ICRISAT-VDSA.

First, I find that there is no wage-size relationship in the ICRISAT-VDSA. Appendix Table 6 decomposes the markdown-size gradient into the wage-size gradient and the MRPL-size gradient. Wages are flat with respect to size. Thus, markdown dispersion emerges from dispersion in $MRPL$ across plots; the marginal worker is very productive on big plots but gets paid a common village wage. This is consistent with findings on the existence of wage norms in rural economies (Breza and Kaur (2025))[8]. $\eta \to \infty$ replicates this feature of the setting in the model, i.e., jobs at different firms within the private sector of a particular market are perfectly substitutable. Under this parameterization, an equilibrium of the model does not feature wage dispersion within the private sector of a labor market. Firms continue to derive market power from workers substituting imperfectly between the private and workfare sector and across labor markets. Within the private sector, a market-level wage clears supply and demand, and labor is allocated across firms according to labor demand at that wage.

Second, Muralidharan et al. (2023) show that the workfare expansion had bigger employment treatment effects in more concentrated labor markets. The calibration targets the coefficient on $T \times HHI$ as a percentage of baseline private employment. The specification in (18) mirrors the empirical exercise in Muralidharan et al. (2023), except that they construct HHI using landholdings from the SECC census, whereas in the model HHI is constructed

[8] We find evidence of residual wage dispersion in ICRISAT-VDSA, however, this dispersion is not systematically linked to size.

using payroll shares.[9]

Finally, the wage markdown is a share-weighted harmonic average of η, γ, and θ, and the markdown distribution is estimated using the ICRISAT-VDSA (Fact 3). The estimate of $\mu = 0.48$ is close to others obtained in developing-country settings (Felix (2026), Armangué-Jubert et al. (2025), Brooks et al. (2021)).

The remaining parameters are assigned or calibrated as follows. The workfare wage $\bar{w}_j = \bar{w}$ in the baseline economy is calibrated to match the workfare-to-private allocation of labor days of 0.57 ($\int \frac{n_j^w}{n_j^p} dj = 4.5/7.9$) in the data[10], I interpret the workfare wage in the model as the effective workfare wage, adjusted for frictions that impede program access (job quality, bureaucratic costs, inadequate availability of jobs, and inconvenient project locations). In the data, the statutory workfare wage is approximately equal to the average private wage. To rationalize the observed labor allocation, the calibration therefore implies $\bar{w} < W^p$.

α is set to 0.4, which is the estimate obtained using Levinsohn and Petrin (2003). The Pareto tail parameter is assigned to be 2.5, reflecting the well-known fat-tailed distribution of farm sizes. The inverse Frisch elasticity is set to 0.4, toward the lower end of values used in the macro literature. This is motivated by evidence of large and frequent transitions between self-employment and wage employment in developing countries (Donovan et al. (2023))[11]. Finally, I use GHH preferences to eliminate wealth effects on labor supply, consistent with the uncertainty surrounding transfer-induced labor supply responses in developing countries (Breza and Kaur (2025)). Under the linear-in-consumption utility form, all theoretical results from Section 4 continue to hold with $\sigma = 0$:

$$U(C, N) = C - \frac{N^{1+\nu}}{1+\nu}.$$

I implement the workfare expansion by setting $\bar{w}_{post} = \Theta \bar{w}_{pre}$, where Θ is chosen to generate a 30% increase in workfare employment. Thus, the calibration interprets the workfare improvement in Muralidharan et al. (2023) in wage-equivalent terms. Regressions of the following form measure the effects of the workfare expansion on private wages, private employment, and workfare employment;

$$outcome_j = cons + \varphi_T T_j + \varepsilon_j,$$

[9] The model takes the stand that landholding concentration maps directly into concentration measured using payroll shares. A Leontief production technology between land and labor delivers this.

[10] There is substantial spatial heterogeneity in the size of the workfare program in India. Andhra Pradesh, the setting of the randomized workfare expansion, is one of the high-performing states with a larger workfare program than the average state.

[11] Breza and Kaur (2025) emphasize the lack of reliable estimates of labor supply elasticities in developing countries.

where T_j equals one after the workfare expansion and zero before.

Table 1 summarizes the calibration strategy, while Table 2 reports the quantitative implications of the calibrated model. With η set to ∞, the markdown target and the treatment gradient are jointly matched by setting $\theta = 0.026$ and $\gamma = 4.98$. Firms primarily derive market power from workers' inability to move across local labor markets, consistent with evidence on substantial spatial frictions in developing countries (Munshi and Rosenzweig (2016), Asher and Novosad (2020), Bryan et al. (2025)). Since $\gamma > \theta$, workfare creates a meaningful local outside option for workers. The gap between γ and θ is important for the size of the procompetitive effect: it determines the return to moving mass on workfare in the inverse elasticity expression.

I evaluate the calibrated model using two non-targeted moments: the markdown-size relationship documented in Fact 4 and the labor share in Indian agriculture.[12] The calibrated model reproduces a steeper markdown-size gradient than in the data. For one, the estimated markdown-size relationship in ICRISAT-VDSA comes from a sample of 18 villages spread across south and central India, and the survey does not provide enough power to estimate this relationship within Andhra Pradesh. For another, size is measured using plot area in the data but payroll shares in the model. If payroll shares are more compressed than landholdings, area exaggerates differences in firm size and therefore implies a flatter empirical markdown gradient.

The calibrated model predicts that the Indian workfare expansion had procompetitive effects on both private wages and private employment through reductions in wage markdowns. The procompetitive channel accounts for roughly one sixth of the aggregate employment effect and one third of the aggregate private wage effect of the workfare expansion.

5.1 Interpreting the size of procompetitive effects

We define a procompetitive multiplier; how much do household earnings from efficiency gains in the private market go up for every dollar increase in workfare earnings? The workfare expansion in Muralidharan et al. (2023) was achieved by improving non-pecuniary features of the job. In their survey, reported hourly wages in workfare do not change due to the workfare improvement. Hence, the increase in workfare earnings is due to the increase in workfare days instead of wage per day. Using the fact that reported daily wages in workfare

[12] Calculated as total payments to labor (imputing wages for family labor), as a share of total revenue for the year 2011, using ICRISAT-VDSA. The labor share in the model is a non-trivial function of the decreasing returns parameter, markdowns, and misallocation.

and private firms are on average the same in the baseline survey:

$$\frac{\Delta \text{ earnings from private}}{\Delta \text{ earnings from workfare}} = \frac{w^p_{j,post} n^p_{j,post} - w^p_{j,pre} n^p_{j,pre}}{w^p_{j,pre}\left(n^w_{j,post} - n^w_{j,pre}\right)}$$
$$= 0.3408$$

The procompetitive multiplier associated with the Indian workfare expansion was 1.34[13]. As a benchmark, the fiscal multiplier out of transitory transfers is estimated to be about 1.5 in the US (Nakamura and Steinsson (2014)) and 2.5 in rural Kenya (Egger et al. (2022)).

5.2 Output gains from workfare

At the calibrated baseline, setting $\bar{w} = 0$ achieves a no workfare benchmark. We can thus recover the counterfactual level of output in the calibrated economy with no workfare. The baseline level of workfare delivers 6.23% higher output relative to the no workfare benchmark.

5.3 Robustness

I verify the robustness of the headline procompetitive multiplier estimate to alternative calibrations. The baseline calibration uses a low inverse Frisch $\nu = 0.4$. $\{\theta, \gamma\}$ are re-calibrated to jointly match the markdown and the heterogenous treatment effect in HHI for $\nu = 0.8$.

Although a wage-size relation is absent in the data, it could be that large employers provide some non-wage benefits to workers, which are not accounted for in the relationship between measured wage and size. I fix $\eta = 6.96$, which is Berger et al. (2022)'s estimate for the US, and recalibrate $\{\theta, \gamma\}$.

Across alternative calibrations, the estimate of the procompetitive multiplier is 1.3-1.4, with some reallocation between the wage and employment channels.

There is some recent evidence that wage dispersion across firms in villages is eliminated by wage 'norms' (Breza et al. (2019), Breza and Kaur (2025)). It is not clear how wage norms emerge. While the model replicates empirical moments, it relies on the Cournot-Nash equilibrium conduct to pin down the labor allocation and wages. The implications of

[13] Interpreting the workfare expansion as a literal increase in workfare wage delivers:

$$\frac{\Delta \text{ earnings from private}}{\Delta \text{ earnings from workfare}} = \frac{w^p_{j,post} n^p_{j,post} - w^p_{j,pre} n^p_{j,pre}}{\bar{w}_{j,post} n^w_{j,post} - \bar{w}_{j,pre} n^w_{j,pre}}$$
$$= 0.2844$$

Table 1: Calibration Strategy

Parameter	Interpretation	Target / Discipline	Source
Assigned Parameters			
Preferences	GHH	standard	—
ν	Inverse Frisch elasticity	standard	—
ξ	Pareto shape parameter	fat-tailed farm size distribution	—
Calibrated Parameters			
θ	Substitution across villages	wage markdown ($\mu = 0.48$)	ICRISAT-VDSA
η	Substitution across firms	Zero size–wage gradient	ICRISAT-VDSA, Breza and Kaur (2025)
γ	Substitution: workfare vs. private employment	Employment treatment effect gradient w.r.t. HHI	Muralidharan et al. (2023)
$m_j = m$	Number of firms per village	Mean HHI (≈ 0.03)	SECC-AP
α	Returns to scale parameter	estimated DRS	ICRISAT-VDSA
$\bar{w}$	workfare wage	workfare/private labor ratio ($= 0.57$)	Muralidharan et al. (2023)
Θ	Workfare improvement	Workfare employment treatment effect ($= 0.30$)	Muralidharan et al. (2023)

Notes: The table reports the calibration strategy for the model parameters. Workfare/private labor ratio is calculated from the baseline data. All data from Muralidharan et al. (2023) is relevant to the month of June, which is the agricultural lean season. The returns to scale come from the Levinsohn-Petrin estimation outlined under Fact 3. The markdown estimate is the plot-area weighted markdown implied by the Levinsohn-Petrin estimate of β_L.

alternative models of wage norms are not clear and beyond the scope of this paper, but an agenda for future research.

6 Optimal policy

This section illustrates policy-relavant applications of the model.

Consider the problem of a planner constrained to implement equilibrium allocations. The planner can affect the equilibrium allocation by regulating the size of workfare, summarised by the instrument $\Phi_j = \left(1 + \phi_j^{1+\gamma}\right)^{\frac{1}{1+\gamma}}$. Suppose the economy consists of one firm in every village, with identical productivity, the workfare wage is endogenous (assumption 1), so that $\phi_j = \phi$ and preferences are CRRA. Using result 3, the equilibrium of this economy (given workfare wage Φ) is the set of objects $\{y, w, n, \mu, \varepsilon^{-1}\}$ and is uniquely determined by the

Table 2: Calibration and Model Fit

	Moments		**Parameters**	
	Model	Data	Interpretation	Value
Assigned / Estimated Parameters				
			inverse Frisch (ν)	0.4
			Pareto shape (ξ)	2.5
			decreasing returns (α)	0.4
			number of labor markets (J)	2000
Targeted Moments and Calibrated Parameters				
workfare/market labor ratio	0.574	0.57	$\bar{w}$	
mean HHI	0.038	0.03	number of firms (m)	33
wage wrt size	0.00	0.00	subs. across firms (η)	∞
markdown μ	0.48	0.48	subs. across villages (θ)	0.026
coef. $T \times HHI$	0.579	0.58	subs. workfare/private (γ)	4.97
workfare labor treat effect	0.30	0.30	workfare improvement (Θ)	1.079
Untargeted Moments				
Labor share	0.19	0.22		
Elasticity of markdowns wrt size	-0.49	-0.15		
Decomposition	*Procompetitive Effect*	*Total Effect*		
Market employment effect	0.0287	0.18		
Market wage effect	0.0289	0.10		

Notes: The table reports the calibration strategy and model fit. The first block reports parameters assigned from the literature or estimated outside the model. The second block reports moments targeted in calibration alongside the corresponding calibrated parameters. The third block reports untargeted moments used to assess external fit. The final block decomposes the total effect of the workfare expansion into the component attributable to reduced employer market power ("procompetitive effect") and the overall equilibrium effect.

following set of equations.

$$y = zn^{\alpha} \quad w = \frac{\mu y}{n} \quad \Phi^{1-\gamma\nu} w = n^{\nu} y^{\sigma}$$
$$\mu = \frac{1}{1+\varepsilon^{-1}} \quad \varepsilon^{-1} = \left(\frac{1}{\gamma} + \Phi^{-(1+\gamma)}\left(\frac{1}{\theta} - \frac{1}{\gamma}\right)\right)$$

Let $\Gamma(\Phi) = \{(y, n) : \{y, w, n, \mu, \varepsilon^{-1}\}$ is an equilibrium given $\Phi\}$. Then the constrained planner's problem is:

$$\max_{\Phi} U(y, \Phi^{\gamma} n)$$
$$\text{s.t. } (y, n) \in \Gamma(\Phi)$$

Note that $\Phi^{\gamma} n$ is aggregate employment in the simplified economy where private employment at the firm is n (equation 5 in the aggregation result 2). This problem can be written as

$$\max_{\Phi} U(y(\Phi), \Phi^{\gamma} n(\Phi))$$

with the first order condition

$$U_1 \frac{dy}{d\Phi} + U_2 \left[\gamma \Phi^{\gamma-1} n(\Phi) + \Phi^{\gamma} \frac{dn}{d\Phi}\right] = 0 \qquad (20)$$

(20) characterises the planner's trade-off. Increasing the size of workfare increases aggregate output by reducing the markdown inefficiency. However, this occurs at the cost of increased labor hours spent. The increase in labor hours spent at firms is efficient, since it is consistent with the household's and firms' first order conditions. Increase in labor hours spent in workfare is inefficient, since workfare produces no output. However, the aggregate gain from spending wasteful labor hours in workfare is the disciplining effect it has on firms, whereby firms come closer to the efficient benchmark. The household only responds to the relative wage in workfare and the private firms in determining its labor allocation. The planner internalizes the efficiency loss from increased labor hours spent at the unproductive activity. (20) can be written as,

$$y(\Phi)^{-\sigma}\frac{dy}{d\Phi} - (\Phi^{\gamma}n(\Phi))^{\nu}\left[\gamma\Phi^{\gamma-1}n(\Phi) + \Phi^{\gamma}\frac{dn(\Phi)}{d\Phi}\right] = 0$$

which can be further simplified as,

$$\alpha z^{1-\sigma}n(\Phi)^{-\alpha(\sigma-1)-1}\frac{dn(\Phi)}{d\Phi} - n(\Phi)^{\nu}\Phi^{\gamma\nu}\gamma\Phi^{\gamma-1}n(\Phi) - n(\Phi)^{\nu}\Phi^{\gamma\nu}\Phi^{\gamma}\frac{dn(\Phi)}{d\Phi} = 0 \tag{21}$$

The appendix derives expressions for $n(\Phi)$, $\frac{dn}{d\Phi}$

$$n(\Phi) = \left[\Phi^{1-\gamma\nu}\alpha\mu z^{1-\sigma}\right]^{\frac{1}{\alpha(\sigma-1)+\nu+1}}$$
$$\frac{dn}{d\Phi} = \left\{\frac{1}{\alpha(\sigma-1)+\nu+1}\left[(1-\gamma\nu) + \frac{dlog\mu}{dlog\Phi}\right]\right\}\frac{n(\Phi)}{\Phi}$$

Together with

$$\mu = \frac{1}{1+\varepsilon^{-1}} \quad \varepsilon^{-1} = \left(\frac{1}{\gamma} + \Phi^{-(1+\gamma)}\left(\frac{1}{\theta} - \frac{1}{\gamma}\right)\right)$$

(21) can be solved for the constrained optimal Φ.

6.1 Optimal size when workfare is unproductive

Does the planner have an interior solution for workfare scale even when workfare is completely unproductive? Yes, if the inefficiency due to labor market power is sufficiently high. Appendix Figure 5 illustrates comparative statics of optimal workfare in an example economy. Optimal workfare scale is larger with strong decreasing returns to scale, low substitutability between workfare and private jobs, higher frictions to mobility between local labor markets and larger Frisch elasticity of labor supply. The gains from having any workfare disappear when the elasticity of substitution across local labor markets is large enough.

The insight here goes beyond workfare programs: if labor market power is sufficiently large, completely unproductive public employment may deliver efficiency gains. This is especially relevant in the context of recent debates on the size of the public sector in the US.

I solve for optimal workfare in the calibrated economy presented in section 5. At the calibrated baseline, I allow the planner to set a workfare wage $\bar{w}$ that maximizes the GHH objective. So instead of implementing the workfare improvement in Muralidharan et al. (2023), I implement the planner's constrained optimum. In the calibrated baseline, the constrained planner optimally eliminates workfare. This is because the welfare loss due to increased hours outweighs the welfare gains from increased output. As the wage markdown goes up, efficiency losses due to labor market power increase and the constrained planner has an interior solution for workfare (Appendix Figure 6).

6.2 How productive should workfare be to justify observed size?

The productivity of public assets created through workfare is hard to measure. This paper makes the case that the planner may want to implement some amount of workfare even if it is unproductive; however, the model implies that in the calibrated economy, the planner optimally eliminates workfare. The model can be used to invert the observed scale of workfare for the level of workfare productivity that rationalizes it as the planner's optimum.

Suppose workfare is productive. Workfare operates a production technology $y_w^j = z_w \left(n_w^j\right)^{\alpha_w}$. However, workfare does not set the wage subject to any objective; the planner exogenously sets the workfare wage to maximize social welfare. Every $(\bar{w}, z_w)$ delivers a certain $scale(\bar{w}; z_w) = \int \frac{n_j^w}{n_j^p} \, dj$[14]. I compute equilibrium and associated welfare over a grid of $(z_w, \bar{w})$, and for every $\bar{w}$ recover the lowest z_w such that $scale(\bar{w}; z_w) = 0.57$, which is the ratio in the baseline. If returns to scale in the workfare technology are identical to the estimated value for the rest of the economy ($\alpha_w = 0.4$), workfare needs to be 2.5 times as productive as the median firm. If returns to scale are much higher, say $\alpha_w = 0.9$, workfare needs to be 0.93 times as productive as the median firm. As labor market power intensifies, the procompetitive gains from workfare become larger, and the level of workfare productivity needed to justify any given workfare scale goes down.

[14] Workfare output is added to aggregate consumption and aggregate output in the goods market clearing condition. With GHH preferences, the size of workfare output does not matter for the equilibrium, only the workfare wage does. So we need to compute equilibrium over the grid of $\bar{w}$ only once, and then compute welfare at different $(\bar{w}, z_w)$ pairs.

6.3 Workfare relative to other labor market interventions

How does workfare compare with standard interventions undertaken to counteract labor market power? I consider the case of a minimum wage. Minimum wages act by constraining wage-setting by firms. Appropriately set, the minimum wage can increase employment and wages by making the firm a price-taker. Set too high, the minimum wage shrinks firms and reduces aggregate output. Result 3 shows that workfare behaves like the appropriately set minimum wage in terms of its observable implications under parametric conditions on the environment. Minimum wages have the biggest efficiency effects at the least productive firms; workfare programs have the biggest efficiency effects at the most productive firms provided markdowns and payroll shares do not covary one for one (Result 5). Minimum wages can be misallocative over some range if the wages of unconstrained productive firms do not respond one-for-one to the wages of constrained less productive firms (Berger et al. (2025)). Workfare programs generate spillovers by allocating workers to the public project. Provided the public project is not the least productive (relative to the set of firms), workfare potentially has smaller efficiency costs due to misallocation.

I consider the calibrated baseline economy, and eliminate workfare to recover the no-workfare benchmark. I compute welfare from various levels of the minimum wage (including the optimal minimum wage) in the no-workfare benchmark. The minimum wage economy is solved following Berger et al. (2025), and involves a set of minimum wage constraints on firms and firm-specific rationing constraints on the household (employment at the firm is the minimum between labor supply and labor demand). The characterisation of the economy in terms of shadow wages and shadow markdowns (wages and markdowns adjusted for the multipliers) delivers a convenient formulation mirroring the characterisation of the no-minimum wage economy (details are outlined in the appendix). I compare welfare from implementing various levels of the minimum wage with welfare from implementing the optimal level of workfare at three different workfare productivity levels (workfare is unproductive, and once or twice as productive as the median firm).

Figure 4 summarises findings[15] . At low levels of the minimum wage, all firms are unaffected and welfare is the same as the no policy benchmark. As the minimum wage goes up, firms move up their labor supply curve; this is the region in which increase in the minimum wage narrows the wage markdown and generates an increase in aggregate output. After some

[15] I have not yet computed the minimum wage economy with $\eta \to \infty$ limit. The figure displayed uses the calibration in Section 5, except that it replaces $\eta = \infty$ with $\eta = 30$. The high value of η generates little wage dispersion and closely approximates the $\eta \to \infty$ limit.

point, rationing constraints activate as labor supply exceeds labor demand at the minimum wage. Further increase in the minimum wage reduce aggregate output, as firms move up their labor demand curve. Figure 4 shows that welfare gains from the optimal minimum wage exceed welfare gains from optimal workfare for reasonable levels of workfare productivity. However, modestly productive workfare delivers welfare gains relative to the minimum wage, when the minimum wage is not optimally set. This is especially relevant in the context of developing countries where the enforcement of minimum wage laws may be very weak, and political economy considerations limit the ability of governments to set high minimum wages.

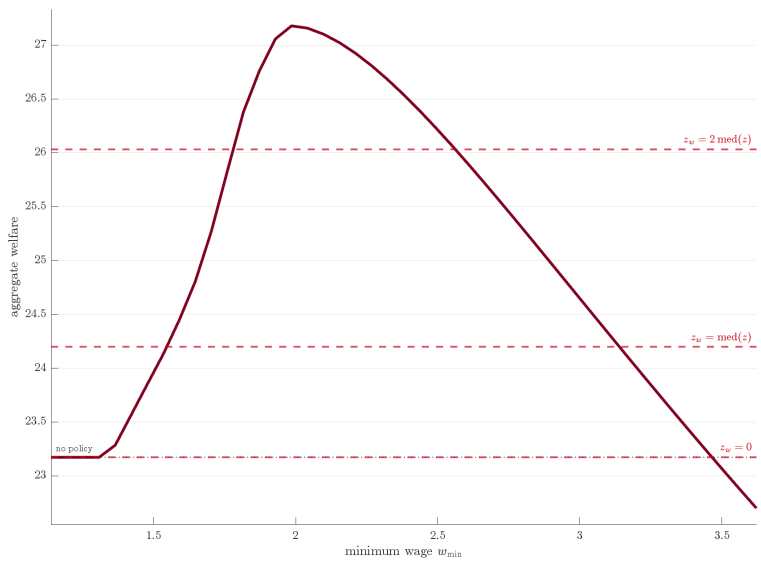

Figure 4: The thick line traces out welfare from the minimum wage with level specified on the horizontal axis. The dashed lines mark the level of welfare from optimal workfare scale when workfare is unproductive, as productive as the median firm and twice as productive as the median firm.

7 Conclusion

Workfare programs are commonly viewed as redistributive policies. This paper studies the role of workfare as procompetitive policy: by creating an outside option for workers, workfare reduces employer labor market power and delivers efficiency gains. In a model of oligopsonistic competition with workfare, I derive predictions for how workfare affects observable macroeconomic aggregates, and how these predictions vary in markets with higher concentration. I devise a way of quantifying the model, combining original evidence from ICRISAT-VDSA with experimental moments from a randomized workfare expansion in the Indian state of Andhra Pradesh.

Calibrated to the experimental setting of Muralidharan et al. (2023), I find that that the workfare expansion in India had substantial procompetitive effects: for every dollar increase in household incomes due to the workfare expansion, earnings from the private market went up by 34 cents due to the reduction in employer market power. The observed level of workfare increased output 6.23% relative to a no-policy counterfactual. Nonetheless, a constrained planner would want to eliminate workfare in the calibrated economy. This is because the efficiency gains from workfare do not compensate for the utility loss due to hours spent on an unproductive public project. If the workfare technology produces output with the same returns to scale as the private economy, workfare would have to be about two and a half times as productive as the median firm to justify the observed scale of the program. The optimal minimum wage welfare-dominates workfare at modest levels of workfare productivity; however, if not optimally set the minimum wage could be sometimes worse than implementing the optimal scale of workfare.

This paper focuses on the procompetitive effects of workfare; more generally, one can study the optimal design of social policy in an economy that features both market power and rich household heterogeneity (Boar and Midrigan (2025),Berger et al. (2022)). On measurement, empirical estimates of wage markdowns combine the effect of market power with the effect of size-dependent frictions or financial frictions. Model-based ways to separately identify these effects would be informative. The role of public employment relative to minimum wages, especially in its effect on misallocation is not understood. The conceptual framework in this paper can be extended to speak to that issue.

8 Appendix

8.1 Bias-corrected markdowns

We follow Levinsohn and Petrin (2003) to bias-correct the labor elasticity from (1), reproduced here as

$$\log Y_{i,t} = \beta_L \log L_{i,t} + \beta_T \log T_{i,t} + \beta_M \log M_{i,t} + \omega_{i,t} + \xi_{i,t}. \tag{22}$$

Labor is a "free" input, chosen contemporaneously with the realization of $\omega_{i,t}$. Land is predetermined—the size of the cultivated plot is fixed at the start of the season. Materials use is assumed frictionless and strictly monotone in $\omega_{i,t}$, holding land fixed,

$$M_{i,t} = f(T_{i,t}, \omega_{i,t}),$$

so that f can be inverted,

$$\omega_{i,t} = h(T_{i,t}, M_{i,t}),$$

and substituted into the production function to obtain

$$\log Y_{i,t} = \beta_L \log L_{i,t} + \varphi(\log T_{i,t}, \log M_{i,t}) + \xi_{i,t},$$

where

$$\varphi(t, m) \equiv \beta_T t + \beta_M m + h(t, m)$$

folds the state and proxy elasticities together with unobserved productivity.

Stage 1. We approximate $\varphi(\log T_{i,t}, \log M_{i,t})$ using a second-order polynomial in $(\log T_{i,t}, \log M_{i,t})$ with all interactions, and estimate the resulting partial-linear specification. Variation in $\log L_{i,t}$, which lies outside the polynomial, identifies β_L. The individual elasticities β_T and β_M are not identified in this stage: both are absorbed into φ alongside the productivity control $h(\cdot)$.

Stage 2. Given any candidate β_T, recover unobserved productivity as

$$\widehat{\omega}_{i,t}(\beta_T) = \widehat{\varphi}_{i,t} - \beta_T \log T_{i,t}.$$

Assuming a first-order Markov process

$$\omega_{i,t} = g(\omega_{i,t-1}) + \eta_{i,t},$$

with g likewise approximated by a polynomial, the innovation $\eta_{i,t}$ is orthogonal to objects predetermined with respect to period t. Predeterminedness of land delivers the moment condition

$$E[\eta_{i,t} \log T_{i,t}] = 0,$$

which we exploit in a GMM step to identify β_T.

A note on β_M. The materials elasticity is not separately identified by the Levinsohn–Petrin procedure. Because materials serve as the proxy for the private signal, $\log M_{i,t}$ enters both through the input's own elasticity ($\beta_M \log M_{i,t}$) and through the productivity control $h(\log T_{i,t}, \log M_{i,t})$, so the two cannot be disentangled without additional assumptions Ackerberg et al. (2015). We therefore leave β_M unreported. This is inconsequential for the object of interest—the wage markdown—which depends only on β_L.

Implementation notes. We implement the procedure using `prodest::prodestLP` in R Rovigatti and Mollisi (2018). The unit of observation is the plot, and the time index is the growing season (Kharif or Rabi within a year), so consecutive observations correspond to consecutive seasons. Within each plot-season cell, labor hours, materials expenditure, revenue, and cultivated area are summed across parcels within a plot, yielding a single observation per (plot, season) pair. Land $T_{i,t}$ is defined as the total cultivated area in season t; because this is chosen at the start of the season and does not adjust in response to within-season productivity shocks $\omega_{i,t}$, it satisfies the predeterminedness restriction underlying the moment condition. We restrict attention to plots observed in at least two consecutive seasons so that a lag is available for each observation entering Stage 2. The polynomial approximations for both $\varphi(\cdot)$ and the Markov process $g(\cdot)$ are second-order, following the package default.

Table 3: Production function estimates

	(1) OLS (saturated FE)	(2) Levinsohn–Petrin
$\log L_{i,t}$	0.492^{***}	0.403^{***}
	(0.083)	(0.016)
Observations	11,647	7,018
Unit of observation	parcel × season × year	plot × season
Plot FE	Yes	–
Village × year × season × crop FE	Yes	–
SE clustered at	village	bootstrap ($R = 200$)

Notes. Column (1) reports OLS estimates of the production function with plot and village × year × season × main-crop fixed effects; standard errors are clustered at the village level ($G = 18$). Column (2) reports the Levinsohn–Petrin estimator (`prodest::prodestLP`) with growing season as the time index and cultivated area treated as predetermined; bootstrap standard errors use $R = 200$ replications. The materials elasticity β_M is not separately identified by the Levinsohn–Petrin procedure — because materials serve as the proxy for the private signal, $\log M$ enters the Stage-1 polynomial both through its own elasticity and through the productivity control, and the two contributions cannot be disentangled without additional assumptions (Ackerberg et al., 2015). This is inconsequential for the wage markdown, which requires only β_L.
$^{*}p < 0.1,^{**}p < 0.05,^{***}p < 0.01$.

Table 4: Markdown–size relationship

	(1) Parcel level	(2) Plot level
$\log(\text{area}_{i,t})$	-0.175^{***}	-0.153^{***}
	(0.024)	(0.022)
Observations	7,733	6,225
Village × year × season × crop FE	Yes	Yes
SE clustered at	village	village

Notes. Dependent variable is $\log \mu$, with μ computed at the parcel level using the Levinsohn–Petrin estimate $\beta_L = 0.403$. Sample: hiring parcel–season–year cells after a 5/95 percentile trim on μ and dropping parcels with $\mu > 1$. Column (1) treats each parcel × season × year cell as one observation. Column (2) collapses parcels to the (plot × season × year) level: $\bar{\mu}$ is the area-weighted mean of the surviving parcels' μ, and area is the summed cultivated area on the plot in the season. Both regressions absorb village × year × season × main-crop fixed effects with cluster-robust SEs at the village level ($G = 18$). $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

Table 5: Materials share of revenue and plot size

	(1) Parcel level	(2) Plot level
$\log(\text{area}_{i,t})$	+0.007	+0.012
	(0.019)	(0.015)
Observations	7,733	6,225
Village × year × season × crop FE	Yes	Yes
SE clustered at	village	village

Notes. Dependent variable is $\log(M/\text{revenue})$, the log ratio of materials expenditure to revenue. Sample: identical to Table 4 — hiring parcel– season–year cells after a 5/95 percentile trim on μ and dropping parcels with $\mu > 1$ (using $\beta_L = 0.403$). Column (1) is at the parcel level. Column (2) collapses to the (plot × season × year) level using the ratio of summed materials to summed revenue on the plot in the season. Both regressions absorb village × year × season × main-crop fixed effects with cluster-robust SEs at the village level ($G = 18$). Neither coefficient is statistically distinguishable from zero. $^{*}p < 0.1,^{**} p < 0.05,^{***} p < 0.01$.

8.2 Labor supply

Taking first order conditions wrt n_{ij} for $j = 1...m_{j-1}$ and n_j^w;

$$-U_N \frac{dN}{dn_j}\frac{dn_j}{dn_j^p}\frac{dn_j^p}{dn_{ij}} = U_C w_{ij}$$

$$-U_N \frac{dN}{dn_j}\frac{dn_j}{dn_j^w} = U_C \bar{w}$$

Table 6: Decomposition of the markdown–size gradient into wage and productivity channels

Dependent variable	(1) $\log \mu_{i,t}$	(2) $\log w_{i,t}^{\text{hired}}$	(3) $\log\left(\text{rev}_{i,t}/L_{i,t}^{\text{total}}\right)$
$\log(\text{parcel\_area}_{i,t})$	-0.175^{***} (0.024)	-0.007 (0.011)	$+0.169^{***}$ (0.025)
Observations	7,733	7,733	7,733
Village × year × season × crop FE	Yes	Yes	Yes
SE clustered at	village	village	village

Notes. Column (1) reproduces the parcel-level markdown–size gradient from Table 4. Column (2) replaces the dependent variable with the log hired wage; column (3) with log revenue per unit of total labour, which equals log MRPL up to the additive constant $\log \beta_L$. Because $\log \mu = \log w^{\text{hired}} - \log \beta_L - \log(\text{rev}/L^{\text{total}})$ and $\log \beta_L$ is absorbed by the fixed effects, the estimates satisfy $\widehat{\gamma}_\mu = \widehat{\gamma}_w - \widehat{\gamma}_{\text{rev}/L}$ ($-0.175 = -0.007 - 0.169$, up to rounding). All regressions absorb village × year × season × main-crop fixed effects with cluster-robust standard errors at the village level ($G = 18$). Sample: hiring parcel–season–year cells after a 5/95 percentile trim on μ and dropping parcels with $\mu > 1$ (using LP $\beta_L = 0.403$). $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

which simplify to

$$\frac{-U_N}{U_C} N^{\frac{-1}{\theta}} n_j^{\frac{1}{\theta}} n_j^{\frac{-1}{\gamma}} (n_j^p)^{\frac{1+\gamma}{\gamma}} = \sum_i^{m_j} w_{ij} n_{ij} \tag{23}$$

$$\frac{-U_N}{U_C} N^{\frac{-1}{\theta}} n_j^{\frac{1}{\theta}} n_j^{\frac{-1}{\gamma}} (n_j^w)^{\frac{1+\gamma}{\gamma}} \delta = \bar{w} n_j^w \tag{24}$$

Adding up (23) and (24),

$$\frac{-U_N}{U_C} N^{\frac{-1}{\theta}} n_j^{\frac{1}{\theta}} n_j^{\frac{-1}{\gamma}} n_j^{\frac{\gamma+1}{\gamma}} = w_j^p n_j^p + \bar{w} n_j^w \tag{25}$$

$$\frac{-U_N}{U_C} N^{\frac{-1}{\theta}} n_j^{\frac{1+\theta}{\theta}} = w_j n_j \tag{26}$$

$$\frac{-U_N}{U_C} N^{\frac{-1}{\theta}} \int_0^1 n_j^{\frac{1+\theta}{\theta}} dj = \int_0^1 w_j n_j dj$$

$$\frac{-U_N}{U_C} N^{\frac{-1}{\theta}} N^{\frac{\theta+1}{\theta}} = WN$$

$$\frac{-U_N}{U_C} = W \tag{27}$$

Substituting (27) into (23),

$$w_{ij} = \left(\frac{n_{ij}}{n_j^p}\right)^{\frac{1}{\eta}} \left(\frac{n_j^p}{n_j}\right)^{\frac{1}{\gamma}} \left(\frac{n_j}{N}\right)^{\frac{1}{\theta}} W$$

We derive some relations that will help in the following derivations. Using (26),

$$WN^{\frac{-1}{\theta}} n_j^{\frac{1}{\theta}} = w_j$$

$$n_j = \left(\frac{w_j}{W}\right)^{\theta} N \tag{28}$$

Using (23),

$$
\begin{aligned}
WN^{\frac{-1}{\theta}} n_j^{\frac{1}{\theta}} n_j^{\frac{-1}{\gamma}} (n_j^p)^{\frac{1+\gamma}{\gamma}} &= w_j^p n_j^p \\
W\left(\frac{n_j}{N}\right)^{\frac{1}{\theta}} \left(\frac{n_j^p}{n_j}\right)^{\frac{1}{\gamma}} &= w_j^p \\
n_j^p &= \left(\frac{w_j^p}{W}\right)^{\gamma} \left(\frac{N}{n_j}\right)^{\frac{\gamma}{\theta}} n_j \qquad (29)
\end{aligned}
$$

Using (24),

$$
\begin{aligned}
WN^{\frac{-1}{\theta}} n_j^{\frac{1}{\theta}} n_j^{\frac{-1}{\gamma}} (n_j^w)^{\frac{1}{\gamma}} \delta &= \bar{w} \\
n_j^w &= \left(\frac{\bar{w}}{\delta W}\right)^{\gamma} N^{\frac{\gamma}{\theta}} n_j^{\frac{\theta-\gamma}{\theta}} \qquad (30)
\end{aligned}
$$

Using (29),

$$
\begin{aligned}
n_j^p &= \left(\frac{w_j^p}{W}\right)^{\gamma} N^{\frac{\gamma}{\theta}} n_j^{1-\frac{\gamma}{\theta}} \\
n_j &= \left[\left(\frac{W}{w_j^p}\right)^{\gamma} N^{\frac{-\gamma}{\theta}} n_j^p\right]^{\frac{\theta}{\theta-\gamma}} \qquad (31)
\end{aligned}
$$

Substituting into the first order condition with respect to n_{ij},

$$
\begin{aligned}
WN^{\frac{-1}{\theta}} \left(\left[\left(\frac{W}{w_j^p}\right)^{\gamma} N^{\frac{-\gamma}{\theta}} n_j^p\right]^{\frac{\theta}{\theta-\gamma}}\right)^{\frac{1}{\theta}-\frac{1}{\gamma}} (n_j^p)^{\frac{1}{\gamma}-\frac{1}{\eta}} n_{ij}^{\frac{1}{\eta}} &= w_{ij} \\
WN^{\frac{-1}{\theta}} \left(\left(\frac{W}{w_j^p}\right)^{\gamma} N^{\frac{-\gamma}{\theta}} n_j^p\right)^{\frac{-1}{\gamma}} (n_j^p)^{\frac{1}{\gamma}-\frac{1}{\eta}} n_{ij}^{\frac{1}{\eta}} &= w_{ij} \\
WN^{\frac{-1}{\theta}} \left(\frac{w_j^p}{W}\right) N^{\frac{1}{\theta}} (n_j^p)^{\frac{1}{\gamma}-\frac{1}{\eta}} n_{ij}^{\frac{1}{\eta}} &= w_{ij} \\
\left(\frac{w_{ij}}{w_j^p}\right)^{\eta} n_j^p &= n_{ij} \qquad (32)
\end{aligned}
$$

We can now derive the private sector wage index. Using (32),

$$
\begin{aligned}
w_j^p n_j^p &= \sum_i^{m_j} w_{ij} n_{ij} \\
&= \sum_i^{m_j} w_{ij} \left(\frac{w_{ij}}{w_j^p}\right)^{\eta} n_j^p \\
w_j^p &= \left(\sum_i^{m_j} w_{ij}^{\eta+1}\right)^{\frac{1}{1+\eta}} \qquad (33)
\end{aligned}
$$

Using (29) and (30),

$$
\begin{aligned}
w_j n_j &= w_j^p n_j^p + \bar{w} n_j^w \\
&= w_j^p \left(\frac{w_j^p}{W}\right)^{\gamma} \left(\frac{N}{n_j}\right)^{\frac{\gamma}{\theta}} n_j + \bar{w}\left(\frac{\bar{w}}{\delta W}\right)^{\gamma} N^{\frac{\gamma}{\theta}} n_j^{\frac{\theta-\gamma}{\theta}} \\
&= \left[(w_j^p)^{1+\gamma} + \frac{\bar{w}^{1+\gamma}}{\delta^{\gamma}}\right]\left(\frac{1}{W}\right)^{\gamma} N^{\frac{\gamma}{\theta}} n_j^{\frac{\theta-\gamma}{\theta}} \qquad (34)
\end{aligned}
$$

Using (28), we have that;

$$
\begin{aligned}
n_j &= \left(\frac{w_j}{W}\right)^{\theta} N \\
n_j^{\frac{1}{\theta}} &= \left(\frac{w_j}{W}\right) N^{\frac{1}{\theta}} \\
n_j^{\frac{1}{\gamma}} &= \left(\frac{w_j}{W}\right) N^{\frac{1}{\theta}} n_j^{\frac{-1}{\theta}} n_j^{\frac{1}{\gamma}} \\
w_j^{-1} n_j^{\frac{1}{\gamma}} &= \left(\frac{1}{W}\right) N^{\frac{1}{\theta}} n_j^{\frac{\theta-\gamma}{\theta\gamma}} \\
w_j^{-\gamma} n_j &= \left(\frac{1}{W}\right)^{\gamma} N^{\frac{\gamma}{\theta}} n_j^{\frac{\theta-\gamma}{\theta}} \qquad (35)
\end{aligned}
$$

Substituting (35) into (34),

$$
\begin{aligned}
w_j n_j &= \left[(w_j^p)^{1+\gamma} + \frac{\bar{w}^{1+\gamma}}{\delta^{\gamma}}\right] w_j^{-\gamma} n_j \\
w_j &= \left[(w_j^p)^{1+\gamma} + \frac{\bar{w}^{1+\gamma}}{\delta^{\gamma}}\right]^{\frac{1}{1+\gamma}} \qquad (36)
\end{aligned}
$$

Finally, using (28),

$$
\begin{aligned}
WN &= \int_0^1 w_j n_j dj \\
WN &= \int_0^1 w_j \left(\frac{w_j}{W}\right)^{\theta} N dj \\
W^{1+\theta} &= \int_0^1 w_j^{1+\theta} dj \\
W &= \left(\int_0^1 w_j^{1+\theta} dj\right)^{\frac{1}{1+\theta}} \qquad (37)
\end{aligned}
$$

8.3 Markdowns

We derive the inverse elasticity equation (9) by differentiating the labor supply equation (2). Note that we construct markdowns under a Cournot-Nash equilibrium of the oligopsonistic competition model; firms take labor at other firms and workfare as given when computing their optimal quantity.

$$\begin{aligned}
\frac{\partial logw_{ij}}{\partial logn_{ij}} &= \frac{\partial}{\partial logn_{ij}} \left\{ \frac{1}{\eta} \left[\log n_{ij} - logn_j^p \right] + \frac{1}{\gamma} \left[logn_j^p - logn_j \right] + \frac{1}{\theta} \left[logn_j - logN \right] + logW \right\} \\
&= \frac{1}{\eta} + \frac{\partial logn_j^p}{\partial logn_{ij}} \left(\frac{1}{\gamma} - \frac{1}{\eta} \right) + \frac{\partial logn_j}{\partial logn_{ij}} \left(\frac{1}{\theta} - \frac{1}{\gamma} \right)
\end{aligned}$$

We now obtain the derivatives involved in deriving the inverse elasticity equation (9). We use the definition of n_j^p and (32);

$$\begin{aligned}
\frac{\partial logn_j^p}{\partial logn_{ij}} &= \frac{\partial n_j^p}{\partial n_{ij}} \frac{n_{ij}}{n_j^p} \\
&= \frac{n_{ij}}{n_j^p} \left[(n_j^p)^{\frac{-1}{\eta}} n_{ij}^{\frac{1}{\eta}} \right] \\
&= \frac{n_{ij} n_{ij}^{\frac{1}{\eta}}}{n_j^p (n_j^p)^{\frac{1}{\eta}}} \\
&= \frac{n_{ij} n_{ij}^{\frac{1}{\eta}}}{(n_j^p)^{\frac{1+\eta}{\eta}}} \\
&= \frac{n_{ij} n_{ij}^{\frac{1}{\eta}}}{\sum_i^{m_j} n_{ij}^{\frac{1+\eta}{\eta}}} \\
&= \frac{n_{ij} \left(\frac{w_{ij}}{w_j^p} \right) (n_j^p)^{\frac{1}{\eta}}}{\sum_i^{m_j} n_{ij} \left(\frac{w_{ij}}{w_j^p} (n_j^p)^{\frac{1}{\eta}} \right)} \\
&= \frac{n_{ij} w_{ij}}{\sum_i^{m_j} n_{ij} w_{ij}} \\
&= s_{ij} \qquad (38)
\end{aligned}$$

Using the definition of n_j and (38),

$$\frac{\partial \log n_j}{\partial \log n_{ij}} = \frac{\partial \log n_j}{\partial \log n_j^p} \frac{\partial \log n_j^p}{\partial \log n_{ij}}$$

$$= \left(\frac{n_j^p}{n_j}\right) n_j^{-1/\gamma} \left(n_j^p\right)^{1/\gamma} s_{ij}$$

$$= \left(\frac{n_j^p}{n_j}\right)^{1+\frac{1}{\gamma}} s_{ij} \tag{39}$$

$$= \left\{\left[1 + \left(\frac{\phi^{\gamma+1}}{\delta^\gamma}\right)\right]^{-\frac{\gamma}{\gamma+1}}\right\}^{\frac{\gamma+1}{\gamma}} s_{ij} \tag{40}$$

$$= \left(1 + \left(\frac{\phi^{1+\gamma}}{\delta^\gamma}\right)\right)^{-1} s_{ij} \tag{41}$$

where moving from (39) to (40) involves using the assumption $\bar{w}_j = \phi w_j^p$. Refer (44) below.

Shares can be expressed as, From the firm FOC,

$$w_{ij} = \mu_{ij} \alpha z_{ij} n_{ij}^{\alpha-1}.$$

Using the private labor supply relation,

$$n_{ij} = \left(\frac{w_{ij}}{w_j^p}\right)^\eta n_j^p,$$

we can write

$$w_{ij} = \mu_{ij} \alpha z_{ij} \left[\left(\frac{w_{ij}}{w_j^p}\right)^\eta n_j^p\right]^{\alpha-1}.$$

Rearranging,

$$w_{ij}^{1+\eta(1-\alpha)} = \mu_{ij} \alpha z_{ij} (w_j^p)^{\eta(1-\alpha)} (n_j^p)^{\alpha-1}.$$

Therefore,

$$w_{ij} \propto (\mu_{ij} z_{ij})^{\frac{1}{1+\eta(1-\alpha)}}.$$

Since

$$s_{ij} = \frac{w_{ij} n_{ij}}{\sum_k w_{kj} n_{kj}} = \frac{w_{ij}^{1+\eta}}{\sum_k w_{kj}^{1+\eta}},$$

we obtain

$$s_{ij} = \frac{(\mu_{ij} z_{ij})^{\frac{1+\eta}{1+\eta(1-\alpha)}}}{\sum_k (\mu_{kj} z_{kj})^{\frac{1+\eta}{1+\eta(1-\alpha)}}}$$

Finally, since $\mu_{ij} = \mu(s_{ij})$,

$$s_{ij} = \frac{[\mu(s_{ij}) z_{ij}]^{\frac{1+\eta}{1+\eta(1-\alpha)}}}{\sum_k [\mu(s_{kj}) z_{kj}]^{\frac{1+\eta}{1+\eta(1-\alpha)}}}$$

The derivation of the markdown in terms of the inverse elasticity is straightforward from the firm's first order condition. Thus, the derivation of the fixed point system in shares is complete.

8.4 Aggregation

Closed form aggregation results are available under the assumption $\bar{w}_j = \phi w_j^p$. Substituting $\bar{w}_j = \phi w_j^p$ into the definition of w_j,

$$w_j = \left((w_j^p)^{1+\gamma} + \frac{(\bar{w}_j)^{1+\gamma}}{\delta^\gamma} \right)^{\frac{1}{1+\gamma}}$$

$$w_j = \left((w_j^p)^{1+\gamma} + \frac{(\phi w_j^p)^{1+\gamma}}{\delta^\gamma} \right)^{\frac{1}{1+\gamma}}$$

$$w_j = \left(1 + \frac{\phi^{1+\gamma}}{\delta^\gamma} \right)^{\frac{1}{1+\gamma}} w_j^p \tag{42}$$

Substituting $\bar{w}_j = \phi w_j^p$ in (30) and using (29), we obtain that

$$n_j^w = \left(\frac{\bar{w}_j}{\delta W} \right)^\gamma \left(\frac{N}{n_j} \right)^{\frac{\gamma}{\theta}} n_j$$

$$= \left(\frac{\phi}{\delta} \right)^\gamma \left(\frac{w_j^p}{W} \right)^\gamma \left(\frac{N}{n_j} \right)^{\frac{\gamma}{\theta}} n_j$$

$$= \left(\frac{\phi}{\delta} \right)^\gamma n_j^p \tag{43}$$

And plugging (43) into the definition of n_j yields,

$$n_j = \left((n_j^p)^{\frac{\gamma+1}{\gamma}} + \delta (n_j^w)^{\frac{\gamma+1}{\gamma}} \right)^{\frac{\gamma}{\gamma+1}}$$

$$n_j = \left((n_j^p)^{\frac{\gamma+1}{\gamma}} + \delta \left(\left(\frac{\phi}{\delta} \right)^\gamma n_j^p \right)^{\frac{\gamma+1}{\gamma}} \right)^{\frac{\gamma}{\gamma+1}}$$

$$n_j = \left((n_j^p)^{\frac{\gamma+1}{\gamma}} \left(1 + \delta \left(\frac{\phi}{\delta} \right)^{\gamma+1} \right) \right)^{\frac{\gamma}{\gamma+1}}$$

$$n_j = n_j^p \left(1 + \left(\frac{\phi^{1+\gamma}}{\delta^\gamma} \right) \right)^{\frac{\gamma}{\gamma+1}} \tag{44}$$

Using the definition of N and substituting (43);

$$N = \left(\int_0^1 n_j^{\frac{\theta+1}{\theta}} \right)^{\frac{\theta}{\theta+1}}$$

$$= \left(1 + \left(\frac{\phi^{1+\gamma}}{\delta^\gamma} \right) \right)^{\frac{\gamma}{\gamma+1}} N^p \tag{45}$$

We conjecture and presently verify:

$$W^p = \left(\int_0^1 \left(w_j^p\right)^{1+\theta} \right)^{\frac{1}{1+\theta}} \tag{46}$$

Given the conjecture (46),

$$W = \left(1 + \frac{\phi^{1+\gamma}}{\delta^\gamma} \right)^{\frac{1}{1+\gamma}} W^p \tag{47}$$

Substituting (44), (45), (46), (47) into (25),

$$\begin{aligned} W N^{\frac{-1}{\theta}} n_j^{\frac{1}{\theta}} n_j^{\frac{-1}{\gamma}} n_j^{\frac{\gamma+1}{\gamma}} &= w_j n_j \\ W^p \left(\frac{n_j^p}{N^p} \right)^{\frac{1}{\theta}} n_j^p &= w_j^p n_j^p \\ n_j^p &= \left(\frac{w_j^p}{W^p} \right)^\theta N^p \qquad (48) \end{aligned}$$

Now using the definition of $W^p N^p$ and (48)

$$\begin{aligned} W^p N^p &= \int_0^1 w_j^p n_j^p \\ &= \int_0^1 w_j^p \left(\frac{w_j^p}{W^p} \right)^\theta N^p \\ W^p &= \left(\int_0^1 \left(w_j^p\right)^{1+\theta} \right)^{\frac{1}{1+\theta}} \qquad (49) \end{aligned}$$

verifying the conjecture.

In market j, Berger et al. (2022) have the following six conditions (four firm-level optimality and two market-level aggregation):

$$\begin{aligned} &y_{ij} = z_{ij} n_{ij}^\alpha \quad n_{ij} = \left(\frac{w_{ij}}{w_j} \right)^\eta n_j \quad w_{ij} = \mu_{ij} mrpl_{ij} \\ &mrpl_{ij} = \alpha z_{ij} n_{ij}^{\alpha-1} \quad y_j = \sum_{i=1}^{m_j} y_{ij} \quad w_j = \left(\sum_{i=1}^{m_j} w_{ij}^{1+\eta} \right)^{\frac{1}{1+\eta}} \end{aligned}$$

which deliver

$$y_j = \omega_j z_j n_j^\alpha \quad w_j = \mu_j \alpha z_j n_j^{\alpha-1}$$

where z_j, ω_j, μ_j have the appropriate expressions.

Across markets, Berger et al. (2022) have the following six conditions (four market-level aggregation and two economy-level aggregation)

$$y_j = \omega_j z_j n_j^{\alpha} \quad n_j^p = \left(\frac{w_j}{W}\right)^{\theta} N \quad w_j = \mu_j mrpl_j$$
$$mrpl_j = \alpha z_j n_j^{\alpha-1} \quad Y = \int_0^1 y_j dj \quad W = \left(\int_0^1 w_j^{1+\theta}\right)^{\frac{1}{1+\theta}}$$

which deliver

$$Y = \Omega Z N^{\alpha} \quad W = \mu \alpha Z N^{\alpha-1}$$

where Z, Ω, μ have the appropriate expressions.

Under the assumption $\bar{w}_j = \phi w_j^p$, we can obtain CES-type labor supply equations in the market economy. This makes the market economy in out model isomorphic to the economy set out in Berger et al. (2022). We exploit this property of the model to state equivalent equations for this model, and then use Berger et al. (2022)'s aggregation result.

In market j, we have the following six conditions (four firm-level optimality and two market-level aggregation):

$$y_{ij} = z_{ij} n_{ij}^{\alpha} \quad n_{ij} = \left(\frac{w_{ij}}{w_j^p}\right)^{\eta} n_j^p \quad w_{ij} = \mu_{ij} mrpl_{ij}$$
$$mrpl_{ij} = \alpha z_{ij} n_{ij}^{\alpha-1} \quad y_j = \sum_{i=1}^{m_j} y_{ij} \quad w_j^p = \left(\sum_{i=1}^{m_j} w_{ij}^{1+\eta}\right)^{\frac{1}{1+\eta}}$$

which deliver

$$y_j = \omega_j z_j \left(n_j^p\right)^{\alpha} \quad w_j^p = \mu_j \alpha z_j \left(n_j^p\right)^{\alpha-1}$$

where z_j, ω_j, μ_j have the appropriate expressions.

Across markets, we have the following six conditions (four market-level aggregation and two economy-level aggregation)

$$y_j = \omega_j z_j \left(n_j^p\right)^{\alpha} \quad n_j^p = \left(\frac{w_j^p}{W^p}\right)^{\theta} N^p \quad w_j^p = \mu_j mrpl_j$$
$$mrpl_j = \alpha z_j \left(n_j^p\right)^{\alpha-1} \quad Y = \int_0^1 y_j dj \quad W^p = \left(\int_0^1 \left(w_j^p\right)^{1+\theta}\right)^{\frac{1}{1+\theta}}$$

which deliver

$$Y = \Omega Z \left(N^p\right)^{\alpha} \quad W = \mu \alpha Z \left(N^p\right)^{\alpha-1}$$

where Z, Ω, μ have the appropriate expressions.

8.5 Proofs: wage and employment effects

Assuming away productivity heterogeneity enables us to solve the model in closed form. Suppose each village consists of a single firm with productivity z and workfare. Using result 2, equilibrium firm-level output y, employment n, wage w, markdown μ are a solution to the following system of equations:

$$y = zn^{\alpha} \qquad w = \frac{\mu y}{n} \qquad \Phi^{1-\gamma\nu} w = n^{\nu} y^{\sigma} \qquad \mu = \frac{1}{1+\varepsilon^{-1}} \qquad \varepsilon^{-1} = \left(\frac{1}{\gamma} + \Phi^{-(1+\gamma)}\left(\frac{1}{\theta} - \frac{1}{\gamma}\right)\right)$$

where $\Phi = \left(1 + \frac{\phi^{\gamma+1}}{\delta^{\gamma}}\right)^{\frac{1}{\gamma+1}}$. Solving this system for n and w,

$$w = \Phi^{\gamma\nu-1} z^{\sigma} n^{\alpha\sigma+\nu} \qquad n = \left[\Phi^{1-\gamma\nu} \alpha\mu z^{1-\sigma}\right]^{\frac{1}{\alpha(\sigma-1)+\nu+1}}$$

Taking logs,

$$\begin{aligned} logw &= (\gamma\nu - 1)log\Phi + \sigma logz + (\alpha\sigma + \nu)logn \\ logn &= \frac{1}{\alpha(\sigma-1)+\nu+1}\left[(1-\gamma\nu)log\Phi + log\mu + (1-\sigma)logz\right] \end{aligned}$$

Differentiating with respect to $log\Phi$,

$$\begin{aligned} \frac{dlogw}{dlog\Phi} &= (\gamma\nu - 1) + (\alpha\sigma + \nu)\frac{dlogn}{dlog\Phi} \\ \frac{dlogn}{dlog\Phi} &= \frac{1}{\alpha(\sigma-1)+\nu+1}\left[(1-\gamma\nu) + \frac{dlog\mu}{dlog\Phi}\right] \end{aligned}$$

Since $\alpha(\sigma-1)+\nu+1 > 0$

$$\begin{aligned} \frac{dlogw}{dlog\Phi} > 0 &\iff (\gamma\nu - 1)(1-\alpha) + (\alpha\sigma+\nu)\frac{dlog\mu}{dlog\Phi} > 0 \\ \frac{dlogn}{dlog\Phi} > 0 &\iff (1-\gamma\nu) + \frac{dlog\mu}{dlog\Phi} > 0 \end{aligned}$$

Restating,

$$\begin{aligned} \frac{dlogw}{dlog\Phi} > 0 &\iff \gamma\nu > 1 - \frac{\alpha\sigma+\nu}{1-\alpha}\frac{dlog\mu}{dlog\Phi} \\ \frac{dlogn}{dlog\Phi} > 0 &\iff \gamma\nu < 1 + \frac{dlog\mu}{dlog\Phi} \end{aligned}$$

Remains to calculate $\frac{dlog\mu}{dlog\Phi}$. Let $A = \Phi^{-(1+\gamma)}$ and $B = \frac{1}{\theta} - \frac{1}{\gamma}$. Then $\varepsilon^{-1} = \frac{1}{\gamma} + AB$. Differentiating,

$$\frac{dA}{d\Phi} = -(1+\gamma)\frac{A}{\Phi} \implies \frac{d\varepsilon^{-1}}{d\Phi} = -(1+\gamma)\frac{AB}{\Phi}$$

and hence

$$\frac{d\varepsilon^{-1}}{dlog\Phi} = -(1+\gamma)AB$$

$$\frac{dlog\mu}{dlog\Phi} = \frac{-1}{1+\varepsilon^{-1}}\frac{d\varepsilon^{-1}}{dlog\Phi}$$

$$\frac{dlog\mu}{dlog\Phi} = \frac{(1+\gamma)AB}{1+\varepsilon^{-1}}$$

where $A = \Phi^{-(1+\gamma)}$ and $\varepsilon^{-1} = \frac{1}{\gamma} + AB$.

In the competitive case, $\mu = 1$, so $\frac{dlog\mu}{dlog\Phi} = 0$. Consequently,

$$\begin{aligned}
\frac{dlogn}{dlog\Phi} &= \frac{1-\gamma\nu}{\alpha(\sigma-1)+\nu+1} \\
\frac{dlogw}{dlog\Phi} &= (\gamma\nu-1) + \frac{(\alpha\sigma+\nu)(1-\gamma\nu)}{\alpha(\sigma-1)+\nu+1} \\
&= \frac{(\gamma\nu-1)\alpha(\sigma-1)+(\gamma\nu-1)(\nu+1)+(\alpha\sigma+\nu)(1-\gamma\nu)}{\alpha(\sigma-1)+\nu+1} \\
&= \frac{(\gamma\nu-1)\alpha\sigma-(\gamma\nu-1)\alpha+(\gamma\nu-1)(\nu+1)-(\gamma\nu-1)\alpha\sigma-(\gamma\nu-1)\nu}{\alpha(\sigma-1)+\nu+1} \\
&= \frac{-(\gamma\nu-1)\alpha+(\gamma\nu-1)\nu+(\gamma\nu-1)-(\gamma\nu-1)\nu}{\alpha(\sigma-1)+\nu+1} \\
&= \frac{(\gamma\nu-1)(1-\alpha)}{\alpha(\sigma-1)+\nu+1}
\end{aligned}$$

8.6 Proofs: concentration

The arguments in this section set $\delta = 1$. Using (29) and (30), we have

$$\begin{aligned}
\frac{n_j^w}{n_j^p} &= \left(\frac{\bar{w}_j}{w_j^p}\right)^\gamma && (50) \\
&= \phi_j^\gamma && (51)
\end{aligned}$$

Let $A_j = \left(\frac{n_j^p}{n_j}\right)^{\frac{\gamma+1}{\gamma}}$

$$A_j = \frac{1}{1+\phi_j^{1+\gamma}} = \Phi_j^{-(1+\gamma)}, \quad \frac{n_j^p}{n_j} = \Phi_j^{-\gamma}, \quad \Phi_j \equiv \left(1+\phi_j^{1+\gamma}\right)^{\frac{1}{1+\gamma}} \tag{52}$$

since

$$n_j^{\frac{\gamma+1}{\gamma}} = \left(n_j^p\right)^{\frac{\gamma+1}{\gamma}} + \left(n_j^w\right)^{\frac{\gamma+1}{\gamma}} = \left(n_j^p\right)^{\frac{\gamma+1}{\gamma}}\left[1+\left(\phi_j^\gamma\right)^{\frac{\gamma+1}{\gamma}}\right] = \left(n_j^p\right)^{\frac{\gamma+1}{\gamma}}\left(1+\phi_j^{1+\gamma}\right) \tag{53}$$

We derive the firm level markdown response (result 5).

We first derive how the workfare expansion changes the the weight A_j on the gain $\left(\frac{1}{\theta} - \frac{1}{\gamma}\right)$ inside the inverse elasticity expression. Let $u_j = \phi_j^{1+\gamma}$. Then $A_j = (1+u_j)^{-1}$ and $1 - A_j = \frac{u_j}{1+u_j}$. $\frac{du}{dlog\phi_j} = (1+\gamma)u$ and

$$\frac{dA_j}{dlog\phi_j} = -\frac{1}{(1+u)^2}(1+\gamma)u = -(1+\gamma)\frac{1}{1+u}\frac{u}{1+u} = -(1+\gamma)A_j(1-A_j) \tag{54}$$

Holding shares constant,

$$\begin{aligned}\frac{d\varepsilon_{ij}^{-1}}{dlog\phi_j} &= s_{ij}\left(\frac{1}{\theta} - \frac{1}{\gamma}\right)\frac{dA_j}{dlog\phi_j} \\ &= -s_{ij}(1+\gamma)A_j(1-A_j)\left(\frac{1}{\theta} - \frac{1}{\gamma}\right) \end{aligned} \tag{55}$$

The Lerner formula is $log\mu_{ij} = -log(1+\varepsilon_{ij}^{-1})$, hence,

$$dlog\mu_{ij} = -\frac{d\varepsilon_{ij}^{-1}}{1+\varepsilon_{ij}^{-1}} = -\mu_{ij}d\varepsilon^{-1}$$

Hence

$$\frac{dlog\mu_{ij}}{dlog\phi_j} = \mu_{ij}s_{ij}(1+\gamma)A_j(1-A_j)\left(\frac{1}{\theta} - \frac{1}{\gamma}\right) \tag{56}$$

which completes the proof of result 5.

Let $q = \frac{1+\eta}{1+\eta(1-\alpha)}$. Recall the definition of the market-level aggregate markdown,

$$\mu_j = \left(\sum_i^{m_j}\left(\frac{z_{ij}}{z_j}\right)^q \mu_{ij}^q\right)^{\frac{1}{q}}$$

Multiplying by z_j^q and totally differentiating, and using the fact that $s_{ij} = \frac{(\mu_{ij}z_{ij})^q}{\sum_k(\mu_{kj}z_{kj})^q}$

$$\begin{aligned}(\mu_j z_j)^q &= \left(\sum_i^{m_j}(\mu_{ij}z_{ij})^q\right)^{\frac{1}{q}} \\ dlog\mu_j &= \sum_i s_{ij}dlog\mu_{ij}\end{aligned} \tag{57}$$

Substituting in (56) into (57),

$$\begin{aligned}\frac{dlog\mu_j}{dlog\phi_j} &= \sum_i s_{ij}\left(\mu_{ij}s_{ij}(1+\gamma)A_j(1-A_j)\left(\frac{1}{\theta} - \frac{1}{\gamma}\right)\right) \\ \frac{dlog\mu_j}{dlog\phi_j} &= (1+\gamma)A_j(1-A_j)\left(\frac{1}{\theta} - \frac{1}{\gamma}\right)\sum_i s_{ij}^2\mu_{ij} \\ \frac{dlog\mu_j}{dlog\phi_j} &= (1+\gamma)A_j(1-A_j)\left(\frac{1}{\theta} - \frac{1}{\gamma}\right)\tilde{H}\end{aligned} \tag{58}$$

which proves result 6.

It is straightforward to show that the model implies the following set of relations:

$$n_j = \Phi_j^{\gamma} n_j^p \qquad w_j = \Phi_j w_j^p \qquad n_j = \left(\frac{w_j}{W}\right)^{\theta} N \qquad w_j^p = \alpha \mu_j z_j \left(n_j^p\right)^{\alpha-1}$$

Putting them together,

$$\begin{aligned}
logn_j^p &= -\gamma log\Phi_j + logn_j \\
&= -\gamma log\Phi_j + \theta(logw_j - logW) + logN \\
&= -\gamma log\Phi_j + \theta(log\Phi_j + logw_j^p - logW) + logN \\
&= (\theta-\gamma) log\Phi_j + \theta\left(log\alpha + log\mu_j + logz_j + (1-\alpha)logn_j^p\right) - \theta logW + logN
\end{aligned}$$

$$\frac{dlogn_j^p}{dlog\phi_j} = \frac{(\theta-\gamma)\frac{dlog\Phi_j}{dlog\phi_j}}{1+\theta(1-\alpha)} + \frac{\theta\frac{dlog\mu_j}{dlog\phi_j}}{1+\theta(1-\alpha)}$$

which proves result 7.

8.7 Computation (GHH, DRS and finite η)

1. Fix $\bar{w}_j$.

2. Enter the iteration with a guess of wages w_{ij}

3. Compute the private wage index:

$$w_j^p = \left(\sum_i w_{ij}^{\eta+1}\right)^{\frac{1}{\eta+1}}$$

4. Compute the village wage index:

$$w_j = \left(w_{pj}^{\gamma+1} + \delta^{-\gamma}\, \bar{w}_j^{\gamma+1}\right)^{\frac{1}{\gamma+1}}$$

5. Compute the aggregate wage index:

$$W = \left(\int_0^1 w_j^{1+\theta} dj\right)^{\frac{1}{1+\theta}}$$

6. Given the wedge $\phi_j = \frac{\bar{w}_j}{w_j^p}$, solve the markdown system to obtain $\{\mu_{ij}\}$.

7. Compute firm labor demand:

$$n_{ij} = \left(\frac{w_{ij}}{\alpha z_{ij} \mu_{ij}} \right)^{\frac{1}{\alpha - 1}}$$

8. Compute total labor supply:

$$N = (W)^{\frac{1}{\nu}}$$

9. Allocate labor across villages:

$$n_j = \left(\frac{w_j}{W} \right)^{\theta} N$$

10. Allocate private labor within village:

$$n_j^p = \left(\frac{w_j^p}{W} \right)^{\gamma} \left(\frac{N}{n_j} \right)^{\gamma/\theta} n_j.$$

11. Impose the within-private CES condition:

$$w_{ij,implied} = \left(\frac{n_{ij}}{n_j^p} \right)^{1/\eta} w_j^p,$$

12. Update $w_{ij,new} = w_{ij} + step * (w_{ij,implied} - w_{ij})$

13. Stop if $||w_{ij,new} - w_{ij}|| < tol$. Else set $w_{ij} = w_{ij,new}$.

14. Check that the goods market clears.

8.8 Computation (GHH, DRS and $\eta \to \infty$ limit)

In the $\eta \to \infty$ limit, private jobs within a village are perfect substitutes, so all firms in a village pay the same wage: $w_{ij} = w_j^p$ for all $i \in j$. The fixed point is on $\{w_j^p\}$ directly.

1. Fix $\bar{w}_j$.

2. Enter the iteration with a guess of village private wages w_j^p.

3. Compute the village wage index:

$$w_j = \left(w_{pj}^{\gamma+1} + \delta^{-\gamma}\, \bar{w}_j^{\gamma+1} \right)^{\frac{1}{\gamma+1}}$$

4. Compute the aggregate wage index:

$$W = \left(\int_0^1 w_j^{1+\theta} dj \right)^{\frac{1}{1+\theta}}$$

5. Given the wedge $\phi_j = \frac{\bar{w}_j}{w_j^p}$, solve the markdown system to obtain $\{\mu_{ij}\}$. (The $(1 - s_{ij})/\eta$ term drops out of ε_{ij}^{-1} in the limit; only the workfare-vs-private and cross-village substitution channels remain.)

6. Compute firm labor demand at the common village wage:
$$n_{ij} = \left(\frac{w_j^p}{\alpha z_{ij} \mu_{ij}} \right)^{\frac{1}{\alpha - 1}}$$

7. Aggregate to village private labor (perfect substitutes: the CES aggregator collapses to a linear sum):
$$n_j^p = \sum_i n_{ij}$$

8. Compute total labor supply:
$$N = W^{1/\nu}$$

9. Allocate labor across villages:
$$n_j = \left(\frac{w_j}{W} \right)^{\theta} N$$

10. Impose household inverse supply on the village (equivalent to the private-share condition $n_j^p = (w_j^p/W)^{\gamma}(N/n_j)^{\gamma/\theta} n_j$, solved for w_j^p):
$$w_{j,implied}^p = W \left(\frac{n_j^p}{\left(\frac{N}{n_j} \right)^{\gamma/\theta} n_j} \right)^{1/\gamma}$$

11. Update $w_{j,new}^p = w_j^p + step * \left(w_{j,implied}^p - w_j^p \right)$

12. Stop if $||w_{j,new}^p - w_j^p|| < tol$. Else set $w_j^p = w_{j,new}^p$.

13. Check that the goods market clears.

8.9 Planner

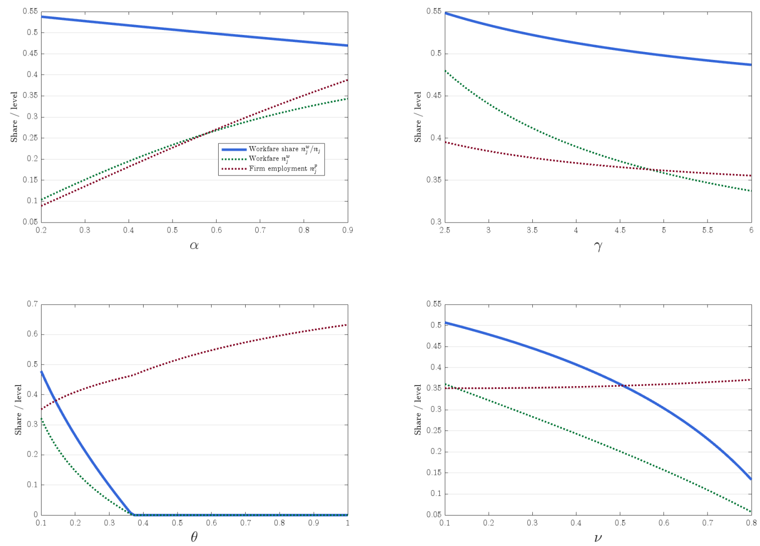

Figure 5: The figure illustrates comparative statics of optimal workfare in an example CRRA economy with $\sigma = 2, \theta = 0.1, \gamma = 6.96, \alpha = 0.8, \nu = 0.2$.

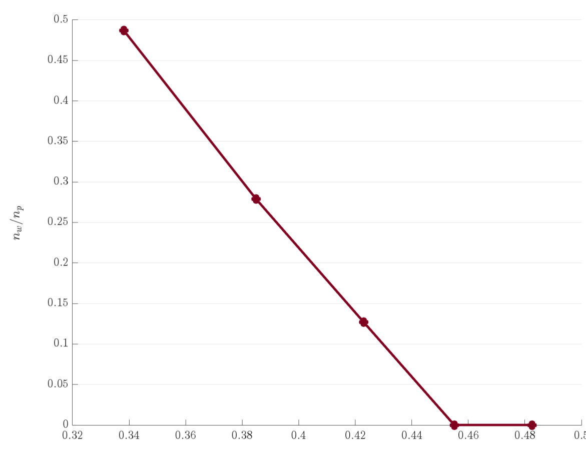

Figure 6: Constrained optimal workfare share in the economies with more labor market power, starting from the calibrated baseline.

8.10 Minimum Wage

Following Berger et al. (2025), we set up equations that characterize the general equilibrium in an economy where the labor market intervention is a minimum wage. The objective is to compare workfare and the minimum wage as alternative procompetitive policies. Let $\tilde{w}_{ij} = p_{ij} w_{ij}$, where $p_{ij} < 1$ implies that the rationing constraint for firm i in village j is binding (slack when $p_{ij} = 1$). The inverse labor supply curve is given by

$$\tilde{w}_{ij} = \left(\frac{n_{ij}}{n_j}\right)^{\frac{1}{\eta}} \left(\frac{n_j}{N}\right)^{\frac{1}{\theta}} \tilde{W}$$

The shadow share of the firm is given by

$$\tilde{s}_{ij} = \frac{\tilde{w}_{ij} n_{ij}}{\sum_i \tilde{w}_{ij} n_{ij}} = \left(\frac{n_{ij}}{n_j}\right)^{\frac{1+\eta}{\eta}} = \frac{\partial log n_j}{\partial log n_{ij}}$$

The firm's problem is

$$\begin{aligned} &\max_{n_{ij}} z_{ij} n_{ij}^{\alpha} - w_{ij} n_{ij} \\ &\text{subject to } w_{ij} = min\left\{ \left(\frac{n_{ij}}{n_j}\right)^{\frac{1}{\eta}} \left(\frac{n_j}{N}\right)^{\frac{1}{\theta}} \tilde{W}, \underline{w} \right\} \end{aligned}$$

where $n_j = \left(\sum_i n_{ij}^{\frac{\eta+1}{\eta}}\right)^{\frac{\eta}{\eta+1}}$.

Unconstrained firms: Suppose ignoring the constraint, the above problem delivers $w_{ij} > \underline{w}$. The Lerner condition delivers

$$\mu_{ij} = \frac{\varepsilon_{ij}}{\varepsilon_{ij} + 1} \quad \frac{1}{\varepsilon_{ij}} = \frac{1}{\eta}\tilde{s}_{ij} + \frac{1}{\theta}(1 - \tilde{s}_{ij})$$

Constrained firms: Consider the above problem subject to the firm paying the minimum wage, and allow for the fact that the firm can always hire less than the amount of labor supplied.

$$\begin{aligned} &max_{n_{ij}} z_{ij} n_{ij}^{\alpha} - \underline{w} n_{ij} \\ &\text{subject to } n_{ij} \leq \left(\frac{\underline{w}}{\tilde{w}_j}\right)^{\eta} \left(\frac{\tilde{w}_j}{\tilde{W}}\right)^{\theta} N \end{aligned}$$

The solution to this problem depends on how $mrpl_{ij}$ compares with $\underline{w}$ at $\hat{n}_{ij}$, which is the ampunt of labor the household supplies at $\underline{w}$.

$$\begin{aligned} n_{ij} &= \left(\frac{\underline{w}}{\tilde{w}_j}\right)^{\eta} \left(\frac{\tilde{w}_j}{\tilde{W}}\right)^{\theta} N \qquad \text{if } \underline{w} \leq \alpha z_{ij} \hat{n}_{ij}^{\alpha-1} \\ &= \left(\frac{\alpha z_{ij}}{\underline{w}}\right)^{\frac{1}{1-\alpha}} \qquad \text{if } \underline{w} > \alpha z_{ij} \hat{n}_{ij}^{\alpha-1} \end{aligned}$$

8.11 Algorithm

We solve the minimum-wage equilibrium by iterating directly on the matrix of firm shadow wages $\{\tilde{w}_{ij}\}$. Each firm is assigned to one of three regions: $r_{ij} \in \{\mathrm{I}, \mathrm{II}, \mathrm{III}\}$, where region I is unconstrained, region II is on the labor supply curve at the minimum wage, and region III is on the labor demand curve at the minimum wage. The household's first-order condition implies $N = \tilde{W}^{1/\nu}$, an identity we enforce at every iteration.

Initialization. Solve the economy without a minimum wage to obtain $\{w_{ij}^{(0)}\}$ and set $\tilde{w}_{ij}^{(0)} = w_{ij}^{(0)}$ for all (i,j). Initialize all firms in region I: $r_{ij}^{(0)} = \mathrm{I}$.

Outer loop (region updates). Given the current region assignment, solve an inner fixed point in $\{\tilde{w}_{ij}\}$; then update regions; then repeat.

Inner loop (fixed point in $\tilde{w}_{ij}$ given regions). Iterate the following block until $\max_{ij} |\tilde{w}_{ij}^{\text{imp}} - \tilde{w}_{ij}| < \varepsilon$:

(1) **Aggregate shadow wages.**

$$\tilde{w}_j = \left(\sum_{i \in j} \tilde{w}_{ij}^{1+\eta} \right)^{\frac{1}{1+\eta}}, \qquad \tilde{W} = \left(\mathbb{E}_j \, \tilde{w}_j^{1+\theta} \right)^{\frac{1}{1+\theta}}.$$

(2) **Household side.** The household FOC delivers aggregate employment and the village-level employment index:

$$N = \tilde{W}^{1/\nu}, \qquad n_j = \left(\frac{\tilde{w}_j}{\tilde{W}} \right)^{\theta} N.$$

(3) **Firm employment from labor supply.** For every firm,

$$n_{ij} = \left(\frac{\tilde{w}_{ij}}{\tilde{w}_j} \right)^{\eta} n_j.$$

At the fixed point this coincides with the region-specific employment defined in the model: it equals the household's supply at the firm's posted wage in regions I and II, and equals the firm's labor demand at $\underline{w}$ in region III, because the region-III implied $\tilde{w}_{ij}$ below is chosen to make these two coincide.

(4) **Shadow shares and markdowns.**

$$\tilde{s}_{ij} = \frac{\tilde{w}_{ij}^{1+\eta}}{\sum_{i' \in j} \tilde{w}_{i'j}^{1+\eta}}, \qquad \frac{1}{\varepsilon_{ij}} = \frac{1 - \tilde{s}_{ij}}{\eta} + \frac{\tilde{s}_{ij}}{\theta}, \qquad \mu_{ij} = \frac{\varepsilon_{ij}}{\varepsilon_{ij} + 1}.$$

(5) **Implied shadow wage by region.**

$$\tilde{w}_{ij}^{\text{imp}} = \begin{cases} \mu_{ij}\, \alpha\, z_{ij}\, n_{ij}^{\alpha-1} & \text{if } r_{ij} = \text{I} \quad \text{(firm FOC)} \\ \underline{w} & \text{if } r_{ij} = \text{II} \quad \text{(supply at the floor; } p_{ij} = 1) \\ \left(\dfrac{n_{ij}^D}{n_j}\right)^{1/\eta} \tilde{w}_j & \text{if } r_{ij} = \text{III} \quad \text{(supply value at } n_{ij}^D) \end{cases}$$

where region III demand is $n_{ij}^D = (\alpha z_{ij}/\underline{w})^{1/(1-\alpha)}$.

(6) **Damped update.**

$$\tilde{w}_{ij} \;\leftarrow\; \tilde{w}_{ij} + \lambda\big(\tilde{w}_{ij}^{\text{imp}} - \tilde{w}_{ij}\big), \qquad \lambda \in (0, 1].$$

Region updates (after the inner loop converges). Compute the marginal revenue product of labor $mrpl_{ij} = \alpha z_{ij} n_{ij}^{\alpha-1}$. Then, for each market j (monotone updates: firms can only move I $\to$ II $\to$ III):

(a) If any firm in region I has $\tilde{w}_{ij} < \underline{w}$, move the firm with the lowest $\tilde{w}_{ij}$ to region II.

(b) If any firm in region II (using the region assignment at the start of this outer iteration) has $mrpl_{ij} < \underline{w}$, move the firm with the lowest $mrpl_{ij}$ to region III.

Convergence. Stop when no firm changes region and the inner-loop tolerance is met. The recovered wages and rationing multipliers are

$$w_{ij} = \begin{cases} \tilde{w}_{ij} & r_{ij} = \text{I} \\ \underline{w} & r_{ij} \in \{\text{II}, \text{III}\} \end{cases}, \qquad p_{ij} = \begin{cases} 1 & r_{ij} \in \{\text{I}, \text{II}\} \\ \tilde{w}_{ij}/\underline{w} & r_{ij} = \text{III} \end{cases}.$$

References

Daniel A Ackerberg, Kevin Caves, and Garth Frazer. Identification properties of recent production function estimators. *Econometrica*, 83(6):2411–2451, 2015.

Francesco Amodio, Pamela Medina, and Monica Morlacco. Labor market power, self-employment, and development. *American Economic Review*, 115(9):3014–3057, 2025.

Tristany Armangué-Jubert, Nezih Guner, and Alessandro Ruggieri. Labor market power and development. *American Economic Review: Insights*, 7(2):177–95, June 2025. doi: 10.1257/aeri.20230564. URL https://www.aeaweb.org/articles?id=10.1257/aeri.20230564.

Sam Asher and Paul Novosad. Rural roads and local economic development. *American economic review*, 110(3):797–823, 2020.

Andrew Atkeson and Ariel Burstein. Pricing-to-market, trade costs, and international relative prices. *American Economic Review*, 98(5):1998–2031, December 2008. doi: 10.1257/aer.98.5.1998. URL https://www.aeaweb.org/articles?id=10.1257/aer.98.5.1998.

David Berger, Kyle Herkenhoff, and Simon Mongey. Labor market power. *American Economic Review*, 112(4):1147–93, April 2022. doi: 10.1257/aer.20191521. URL https://www.aeaweb.org/articles?id=10.1257/aer.20191521.

David Berger, Kyle Herkenhoff, and Simon Mongey. Minimum wages, efficiency, and welfare. *Econometrica*, 93(1):265–301, 2025. doi: https://doi.org/10.3982/ECTA21466. URL https://onlinelibrary.wiley.com/doi/abs/10.3982/ECTA21466.

Timothy Besley and Stephen Coate. Workfare versus welfare: Incentive arguments for work requirements in poverty-alleviation programs. *The American Economic Review*, 82(1): 249–261, 1992. ISSN 00028282. URL http://www.jstor.org/stable/2117613.

Corina Boar and Virgiliu Midrigan. Markups and inequality. *Review of Economic Studies*, 92(5):2828–2860, 2025.

Gideon Bornstein and Alessandra Peter. Nonlinear pricing and misallocation. *American Economic Review*, 115(11):3853–3908, November 2025. doi: 10.1257/aer.20230168. URL https://www.aeaweb.org/articles?id=10.1257/aer.20230168.

Emily Breza and Supreet Kaur. Labor markets in developing countries. *Annual Review of Economics*, 17, 2025.

Emily Breza, Supreet Kaur, and Nandita Krishnaswamy. Scabs: The social suppression of labor. 2019.

Wyatt J. Brooks, Joseph P. Kaboski, Yao Amber Li, and Wei Qian. Exploitation of labor? classical monopsony power and labor's share. *Journal of Development Economics*, 150: 102627, 2021. ISSN 0304-3878. doi: https://doi.org/10.1016/j.jdeveco.2021.102627. URL https://www.sciencedirect.com/science/article/pii/S0304387821000043.

Gharad T Bryan, Kyra Frye, and Melanie Morten. Spatial economics for low-and middle-income countries. Technical report, National Bureau of Economic Research, 2025.

Francisco J Buera, Joseph P Kaboski, and Yongseok Shin. The macroeconomics of microfinance. *The Review of Economic Studies*, 88(1):126–161, 08 2020. ISSN 0034-6527. doi: 10.1093/restud/rdaa047. URL https://doi.org/10.1093/restud/rdaa047.

Kevin Donovan, Will Jianyu Lu, and Todd Schoellman. Labor market dynamics and development. *The Quarterly Journal of Economics*, 138(4):2287–2325, 2023.

Chris Edmond, Virgiliu Midrigan, and Daniel Yi Xu. Competition, markups, and the gains from international trade. *American Economic Review*, 105(10):3183–3221, October 2015. doi: 10.1257/aer.20120549. URL https://www.aeaweb.org/articles?id=10.1257/aer.20120549.

Dennis Egger, Johannes Haushofer, Edward Miguel, Paul Niehaus, and Michael Walker. General equilibrium effects of cash transfers: experimental evidence from kenya. *Econometrica*, 90(6):2603–2643, 2022.

Ester Faia, Benjamin Lochner, and Benjamin Schoefer. Monopsony, markdowns, and minimum wages. Technical report, National Bureau of Economic Research, 2026.

Mayara Felix. Trade, labor market concentration, and wages. Technical report, National Bureau of Economic Research, 2026.

Andrew D Foster and Mark R Rosenzweig. Are there too many farms in the world? labor market transaction costs, machine capacities, and optimal farm size. *Journal of Political Economy*, 130(3):636–680, 2022.

Chang-Tai Hsieh and Peter J Klenow. Misallocation and manufacturing tfp in china and india. *The Quarterly journal of economics*, 124(4):1403–1448, 2009.

Clément Imbert and John Papp. Labor market effects of social programs: Evidence from india's employment guarantee. *American Economic Journal: Applied Economics*, 7(2):233–63, April 2015. doi: 10.1257/app.20130401. URL https://www.aeaweb.org/articles?id=10.1257/app.20130401.

Clément Imbert and John Papp. Costs and benefits of rural-urban migration: Evidence from india. *Journal of Development Economics*, 146:102473, 2020. ISSN 0304-3878. doi: https://doi.org/10.1016/j.jdeveco.2020.102473. URL https://www.sciencedirect.com/science/article/pii/S0304387820300481.

Joseph P Kaboski and Robert M Townsend. A structural evaluation of a large-scale quasi-experimental microfinance initiative. *Econometrica*, 79(5):1357–1406, 2011.

Stefan Klonner and Christian Oldiges. The welfare effects of india's rural employment guarantee. *Journal of Development Economics*, 157:102848, 2022.

James Levinsohn and Amil Petrin. Estimating production functions using inputs to control for unobservables. *The review of economic studies*, 70(2):317–341, 2003.

Kaivan Munshi and Mark Rosenzweig. Networks and misallocation: Insurance, migration, and the rural-urban wage gap. *American Economic Review*, 106(01):46–98, 2016.

Karthik Muralidharan, Paul Niehaus, and Sandip Sukhtankar. Building state capacity: Evidence from biometric smartcards in india. *American Economic Review*, 106(10):2895–2929, October 2016. doi: 10.1257/aer.20141346. URL https://www.aeaweb.org/articles?id=10.1257/aer.20141346.

Karthik Muralidharan, Paul Niehaus, and Sandip Sukhtankar. General equilibrium effects of (improving) public employment programs: experimental evidence from india. *Econometrica*, 91(4):1261–1295, 2023. doi: https://doi.org/10.3982/ECTA18181. URL https://onlinelibrary.wiley.com/doi/abs/10.3982/ECTA18181.

Emi Nakamura and Jón Steinsson. Fiscal stimulus in a monetary union: Evidence from us regions. *American Economic Review*, 104(3):753–792, 2014.

Mark R Rosenzweig. Payoffs from panels in low-income countries: Economic development and economic mobility. *American Economic Review*, 93(2):112–117, 2003.

Martin Rotemberg. Equilibrium effects of firm subsidies. *American Economic Review*, 109 (10):3475–3513, 2019.

Gabriele Rovigatti and Vincenzo Mollisi. PRODEST: Stata module for production function estimation. *Statistical Software Components*, 2018.

Garima Sharma. Collusion among employers in india. Technical report, Working Paper, 2024.

Robert M Townsend. Risk and insurance in village india. *Econometrica: journal of the Econometric Society*, pages 539–591, 1994.

a World Bank. The state of safety nets, honorati, maddelena and gentellini, ugo and yemtsov, ruslan g. Technical report, World Bank, 2015.