Nominal Wage Rigidity in Village Labor Markets*

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Abstract

This paper tests for downward nominal wage rigidity in markets for casual daily agricultural labor in a developing country context. I examine wage and employment responses to rainfall shocks—which shift labor demand—in 500 Indian districts from 1956-2008. First, there is asymmetric wage adjustment: nominal wages rise in response to positive shocks but do not fall during droughts. Second, after transitory positive shocks have dissipated, nominal wages do not return to previous levels—they remain high in future years. Third, inflation moderates these effects: when inflation is higher, real wages are more likely to fall during droughts and after transitory positive shocks. Fourth, wage distortions generate employment distortions: employment is lower in the year after a transitory positive shock than if the positive shock had not occurred; landless laborers experience a 6% employment reduction. Fifth, consistent with misallocation of labor across farms, households with smaller landholdings increase labor supply to their own farms when they are rationed out of the external labor market. These findings indicate that wage rigidity lowers employment levels and increases employment volatility—in a setting with few institutional constraints. Data from a new survey I conducted in two Indian states suggests that agricultural workers and employers: view nominal wage cuts as unfair; are considerably less likely to regard real wage cuts as unfair if they are achieved through inflation rather than nominal cuts; and believe that nominal wage cuts cause effort reductions.

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1 Introduction

This paper empirically examines downward nominal wage rigidity and its employment consequences in a developing country context. Under such rigidities, wages are expected to exhibit three features. First, wages are rigid—they do not adjust fully to productivity shocks. Second, the rigidity is asymmetric—adjustment is hindered particularly in the downward direction. Third, the rigidity applies to nominal wage reductions—real wage cuts are not impeded if they occur through inflation. Put simply, wages resist falling from their current values in nominal terms. Such rigidities, if present, can deepen the impact of recessions and heighten employment volatility. As a result, they have been a focus of much debate in a broad literature on unemployment and business cycle dynamics.[1] In addition, they could help explain apparent labor market imperfections in poor countries, such as labor rationing and differences in labor allocation on small and large farms.[2]

Establishing the presence of downward nominal wage rigidity has posed an empirical challenge. A literature in OECD countries finds evidence based primarily on examining distributions of wage changes (e.g., McLaughlin 1994; Kahn 1997; Dickens et al. 2006). While this approach yields compelling documentation, it is vulnerable to measurement error and requires limiting analysis to workers employed by the same firm in consecutive years.[3] Importantly, it also does not allow for analysis of the employment effects of rigidities–there is limited evidence directly connecting the presence of rigidities to employment distortions. A more direct test would involve examining how wages react to changes in the marginal revenue product of labor, but shifters of this are typically difficult to isolate.[4]

To overcome this challenge, I exploit a feature of agricultural production in developing countries. In this setting, local rainfall variation generates transitory labor demand shocks. I focus on markets for casual daily agricultural labor—a major source of employment in poor countries. To test for

[1]For overviews, see Tobin (1972); Greenwald and Stiglitz (1987); Blanchard (1990); Clarida, Galì, and Gertler (1999); Akerlof (2002); and Galì (2002).

[2]See Rosenzweig (1988) and Behrman (1999) for reviews of the debate on labor market imperfections in this context.

[3]Akerlof, Dickens, and Perry (1996) and Card and Hyslop (1997) provide excellent discussions of measurement challenges associated with the histogram approach.

[4]Holzer and Montgomery (1993) perform analysis in this spirit. They examine correlations of wage and employment growth with sales growth, which they assume reflects demand shifts. They find that wage changes are asymmetric and are small compared to employment changes. Card (1990) uses a different approach in the context of unionized Canadian firms. When nominal wages are explicitly indexed to expected inflation, real wages do not adjust to inflation surprises. As a result, these firms adjust employment down (up) when inflation surprises raise (lower) real wages.

rigidity, I examine market-level wage and employment responses to rainfall shocks in 500 Indian districts from 1956 to 2008.

Wage responses are consistent with downward rigidities. First, wage adjustment is asymmetric. While nominal wages rise robustly in response to positive shocks, they do not fall during droughts on average. Second, transitory positive shocks cause a persistent increase in wages. When a positive shock in one year is followed by a non-positive shock in the following year, wages do not adjust back down—they remain higher than they would have been in the absence of the lagged positive shock.

Third, particularly consistent with *nominal* rigidity, inflation moderates these wage distortions. When inflation is higher, droughts are more likely to result in lower real wages. In addition, transitory positive shocks are less likely to have persistent wage effects. For example, when inflation is above 6%, positive shocks have no impact on future wages. Since local rainfall is uncorrelated with inflation levels, these tests have a causal interpretation.[5] The findings support the hypothesis that inflation "greases the wheels" of the labor market (see, e.g., Tobin 1972; Akerlof, Dickens, and Perry 1996; Card and Hyslop 1997).

When nominal rigidities bind—keeping wages above market clearing levels—this distorts employment. For a given non-positive shock in the current year, a transitory positive shock in the previous year raises current wages without affecting current productivity. This causes a 3% average drop in total worker-days spent in agriculture. This magnitude is equivalent to the employment decrease during a drought. There is heterogeneity in these effects: workers with less land are considerably more likely to be rationed out of the labor market. This is because landed households exhaust their own labor supply on their farms before hiring outside labor, whereas those with little or no land must supply to other farms at the prevailing wage. As a result, landless laborers experience a 6% average drop in employment. Overall, these employment dynamics are consistent with boom and bust cycles in village economies. They also match observations from other contexts that labor markets exhibit relatively large employment volatility and small wage variation.

When workers face rationing in external employment, they increase labor supply to their own farms. Specifically, households in the bottom tercile of landholdings supply 7% more labor to their own land in the year after a positive shock than if the positive shock had not occurred. This

[5] Rainfall shocks are local to small geographic areas and do not affect national price levels—a fact I verify empirically in Section 4.

is consistent with the prediction that in the presence of labor market failures, a household's labor supply decision will not be separable from its decision of how much labor to use on its farm (see, e.g.: Singh, Squire, and Strauss 1986; Benjamin 1992; Udry 1996). The fact that smaller farms tend to use more labor per acre and have higher yields per acre than larger farms has been widely documented in the development literature (e.g. Bardhan 1973). These results support the hypothesis that this relationship can be attributed to separation failures, which lead the marginal product of labor to be lower on smaller farms than larger ones.

Could the above findings be explained by factors other than nominal wage rigidity? For example, if positive shocks have persistent productivity effects, this could explain why wages remain high in the following year. However, in this case, employment should not fall in the next year. Alternately, inter-temporal substitution in labor could explain why positive shocks increase future wages and lower future employment. However, this is not consistent with the inflation results—labor supply shifters should not be affected by inflation. In addition, small farms respond to the decrease in external employment by supplying more intensively to their own farms—this is also inconsistent with the idea that the wage dynamics are driven by a decrease in labor supply in the year after a positive shock. Similar arguments imply that factors such as income effects, migration, or capital investment are also not driving the empirical findings. I argue the pattern of results is most consistent with nominal rigidities.

There is some evidence that wages are less rigid in areas where the costs of rigidity are likely to be higher. Certain crops are especially sensitive to the amount of labor hired—for example, they experience large output losses if not harvested immediately upon reaching maturity. In areas with such crops, price flexibility is particularly important because inefficient labor allocation will lead to especially large profit losses. Consistent with this, districts that grow more labor-sensitive crops are more likely to experience nominal wage cuts during droughts. In addition, while these districts are equally likely to raise wages in response to transitory positive shocks, such shocks are less likely to have persistent wage effects. These results provide suggestive evidence that rigidity is endogenous to local economic conditions.[6]

Having established the presence of nominal rigidity, I explore possible mechanisms using a survey

[6]These findings are only suggestive since planting decisions are endogenous. The causality could also run in the opposite direction: farmers could be more likely to plant labor sensitive crops in areas where there are weaker norms for rigid wages.

I conducted in rural India. A growing body of evidence argues that nominal wage cuts are perceived as unfair, causing decreases in worker productivity.[7] Following Kahneman, Knetsch, and Thaler (1986), I presented 400 agricultural laborers and landed farmers in 34 villages with scenarios about wage setting behavior, and asked them to rate the behaviors as fair or unfair on a 4-point scale. The results suggest that wage cuts strongly violate fairness norms. For example, 62% of respondents thought it was unfair for an employer to cut wages after a surge in unemployment. To examine differences between nominal and real wages, I presented a scenario in which employers cut real wages by 5%, but varied whether this was achieved through a nominal wage cut or inflation. 64% of respondents thought it was unfair to cut nominal wages by 5% during a period of no inflation. In contrast, only 9% of respondents thought it was unfair to raise nominal wages by 5% during a period of 10% inflation. Respondents also displayed a strong belief that workers decrease effort when fairness norms are violated. Consistent with the crop heterogeneity results, in villages with more labor-sensitive crops, respondents were considerably less likely to view wage cuts as unfair. This suggests that fairness norms may form, at least in part, endogenously.

The results point to the relevance of nominal rigidities in a setting with few of the institutional constraints that have received prominence in the existing literature. For example, in villages, minimum wage legislation is largely ignored and formal unions are rare (Rosenzweig 1980; 1988). Wage contracts for casual laborers are typically of short duration (on the order of days) and can more easily reflect recent changes in market conditions. Observing rigidity in such a context is consistent with the potential importance of non-institutional forces such as fairness norms in labor markets.

The rest of the paper proceeds as follows. Section 2 presents a model of nominal wage rigidity. Section 3 lays out the empirical strategy that will be used to test the model's predictions. Section 4 presents the results. Section 5 evaluates whether explanations other than nominal rigidity can explain the results. Section 6 discusses mechanisms for nominal rigidities and presents survey evidence for the role of fairness norms in villages. Section 7 concludes.

[7] Individual responses to a range of scenarios suggest the relevance of nominal variables (Shafir, Diamond, and Tversky 1997). Employers express perceptions that nominal wage cuts damage worker morale, with potential consequences for labor productivity (Blinder and Choi 1990; Bewley 1999). Lab and field studies validate the survey evidence (Fehr, Kirchsteiger, and Riedl 1993; Fehr and Falk 1999; Gneezy and List 2006). See Fehr, Goette, and Zehnder (2009) for a broader discussion of the relevance of fairness preferences in labor markets.

2 Model

In this section, I model a small open economy with decentralized wage setting and exogenous product prices. Rigidities arise because workers view wage cuts below a nominal reference wage as unfair, and retaliate to such cuts by decreasing effort.[8] In the empirical work, the reference wage will be the average nominal wage in the market in the previous period. I use this framework to develop testable implications of fairness preferences on labor market outcomes.

2.1 Set-up

The labor force is comprised of a unit mass of potential workers. All workers are equally productive. They are indexed by parameter ϕ_i, which equals worker i's cost of supplying 1 unit of effective labor. This parameter is distributed uniformly over the interval $\left[0, \overline{\phi}\right]$. The worker's payoff from accepting a nominal wage offer of w equals the utility from consuming her real wage minus the disutility of working:

$$u\left(\frac{w}{p}\right) - \phi_i e \left\{1 + \frac{1-\lambda}{\lambda} I_{\{w<w_R\}}\right\},$$

where p is the price level. The disutility of work equals ϕ_i times the amount of effort, e, exerted by the worker. The term in brackets captures fairness preferences. Workers view working for a wage below an exogenous nominal reference wage, w_R, as unfair. The worker's disutility of work is scaled up by $\frac{1-\lambda}{\lambda} I_{\{w<w_R\}}$, where $I_{\{w<w_R\}}$ is an indicator for whether the wage is below w_R and $\lambda \in (0, 1]$. When $\lambda = 1$, the disutility of work is the same regardless of whether $w < w_R$. As λ decreases, working for a wage below the reference wage imposes larger costs.

A market-wide fairness norm governs workers' effort behavior. The worker usually exerts a standard amount of effort: $e = 1$. However, when she feels treated unfairly by the firm, she reduces

[8] In Section 6, I provide support for this modeling assumption using survey evidence on village fairness norms. I also discuss whether other micro-foundations for rigidity are consistent with the context of the study and empirical results.

her effort to exactly offset the disutility from the fairness violation:

$$e = \begin{cases} 1 & w \geq w_R \\ \lambda & w < w_R \end{cases}. \tag{1}$$

In the model, I take this fairness norm as exogenous.[9] More generally, it can be conceptualized as the reduced form for a strategy in a repeated game. Worker i's payoff from accepting wage offer w reduces to $u\left(\frac{w}{p}\right) - \phi_i$. I normalize the payoff from not working as 0. When all firms offer wage w, aggregate labor supply is given by:

$$L^S = \frac{1}{\phi} u\left(\frac{w}{p}\right). \tag{2}$$

There are J firms (indexed by j), where J is large so that each firm's wage contributes negligibly to the average market wage. Firm j's profits from hiring L_j workers at nominal wage w_j equals:

$$\pi_j = p\theta f\left(eL_j\right) - w_j L_j, \tag{3}$$

where θ is a non-negative stochastic productivity parameter whose realization is common to all firms and $f\left(\bullet\right)$ is a continuous, increasing, twice-differentiable concave function. Note that output depends on effective labor—the number of workers times the effort exerted by each worker.

2.2 Benchmark Case: No Rigidity

I begin by solving the benchmark case in which there are no fairness preferences, i.e., when $\lambda = 1$. In this case, $e = 1$ for all w. Firm j's profits are given by:

$$\pi_j = p\theta f\left(L_j\right) - w_j L_j. \tag{4}$$

[9]This is similar to the conceptualization of worker retaliation in Akerlof and Yellen (1990). They assume an exogenous effort rule according to which workers reduce effort in proportion to how far their wage falls below a perceived fair wage, and examine the implications of this in an economy with inelastically fixed labor supply.

I focus on the symmetric pure strategy Nash Equilibrium, in which all firms offer the same wage:[10]

$$w_j = w^* (\theta, p) \ \forall j,$$

where $w^* (\theta, p)$ will be used to denote the benchmark equilibrium wage level at θ and p. Since firms are identical, they all demand the same amount of labor, $L^* (\theta, p)$. The firm's first order condition is:

$$p\theta f' (L^*) = w^*. \tag{5}$$

This pins down the optimal choice of labor at w^*; since this condition is the same for all firms, all firms will demand the same amount of labor L^*. The market clearing condition is characterized by:

$$JL^* = \frac{1}{\phi} u \left(\frac{w^*}{p} \right). \tag{6}$$

This condition simply equates the amount of aggregate labor demand with aggregate labor supply at (w^*, L^*).

Proposition 1: Market clearing in benchmark case

If workers do not exhibit fairness preferences, the unique pure strategy symmetric Nash Equilibrium will satisfy conditions (5) and (6). The labor market will clear for all realizations of θ.

Proof: See Appendix A. ■

Note that equations (5) and (6) correspond exactly to the conditions in a competitive equilibrium. Combining these equations and taking the derivative of w^* with respect to θ gives $\frac{\partial w^*(\theta,p)}{\partial \theta} > 0$ for all values of θ. Consequently, any decrease in θ will lead to a reduction in the equilibrium wage level.

Corollary 1: Complete adjustment to negative shocks in benchmark case

[10] In villages, it is common for employers to conform to a single prevailing wage for agricultural workers. Section 4 (Table 5) presents evidence in support of this. It is therefore reasonable in this setting to focus on pure strategy symmetric equilibria.

If workers do not exhibit fairness preferences, the wage will adjust downward with a decrease in θ over all θ-values.

2.3 Downward Rigidity at the Reference Wage

I now turn to examine the implications of fairness preferences on labor market outcomes. Firm profits are given by expression (3). Note that for any (w_j, L_j) combination, profits are always weakly lower in the fairness case than the benchmark case.

In the symmetric pure strategy Nash equilibrium:

$$w_j = \overline{w}\left(w_R, \theta, p\right) \; \forall j,$$

where $\overline{w}\left(w_R, \theta, p\right)$ will be used to denote the equilibrium wage level corresponding to reference wage w_R, TFP θ, and price p in the fairness case. All firms demand the same amount of labor, $\overline{L}\left(w_R, \theta, p\right)$. For a given $\overline{w}$, this is pinned down by the firm's first order condition, which exhibits a discontinuity around w_R :

$$\overline{w} = \begin{cases} p\theta f'\left(\overline{L}\right) & \overline{w} \geq w_R \\ p\theta\lambda f'\left(\lambda\overline{L}\right) & \overline{w} < w_R \end{cases}. \tag{7}$$

When $\overline{w} \geq w_R$, this corresponds exactly to the first order condition in the benchmark case. However, when $\overline{w} < w_R$, retaliation by the firm's workers makes them less productive. I assume:

$$f'\left(\overline{L}\right) > \lambda f'\left(\lambda\overline{L}\right) \; for \; \lambda < 1. \tag{8}$$

Condition (8) implies that for a given wage level $\overline{w} < w_R$, firms demand less labor than in the benchmark case. This condition always holds, for example, under Cobb-Douglas production: $f\left(eL\right) = \left(eL\right)^{\alpha}$.

Define θ_R as the unique value of θ at which w_R is the equilibrium wage and the labor market clears. Specifically, θ_R is pinned down by the the following two conditions:[11]

$$\overline{w}\left(w_R, \theta_R, p\right) = w_R$$

$$J\overline{L}\left(w_R, \theta_R, p\right) = \frac{1}{\phi} u\left(\frac{w_R}{p}\right).$$

The next proposition establishes asymmetric adjustment in wages around θ_R.

Proposition 2: Asymmetric adjustment to shocks

In the unique pure strategy symmetric Nash equilibrium:

(i) There exists a $\theta'_R < \theta_R$ such that for all $\theta \in (\theta'_R, \theta_R)$:

$$\overline{w}\left(w_R, \theta, p\right) = w_R \quad \textit{and} \quad J\overline{L}\left(w_R, \theta, p\right) < \tfrac{1}{\phi} u\left(\tfrac{\overline{w}(w_R, \theta, p)}{p}\right) \quad .$$

In addition, $\lim\limits_{\lambda \to 0} \theta'_R = 0$.

(ii) For $\theta \geq \theta_R$, the wage will correspond to the benchmark case and the labor market will clear:

$$\overline{w}\left(w_R, \theta, p\right) = w^*\left(\theta, p\right) \quad \textit{and} \quad J\overline{L}\left(w_R, \theta, p\right) = \tfrac{1}{\phi} u\left(\tfrac{\overline{w}(w_R, \theta, p)}{p}\right) \; .$$

Proof: See Appendix A. ■

For values of θ above θ_R, firms will increase wages smoothly as θ rises. However, for values of θ below θ_R, if firms cut nominal wages, they will suffer profit losses from decreases in worker effort. For sufficiently small decreases in θ below θ_R, it will be more profitable to maintain wages at w_R. Since the wage will remain the same, aggregate labor supply will remain the same. However, the firm's first order condition (7) implies labor demand will fall due to $\theta < \theta_R$, leading to excess supply in the market. Once θ falls to a sufficiently low level, below θ'_R, w_R can no longer be sustained as an equilibrium; equilibrium wages will be below w_R and the labor market will clear. Note that θ'_R will be lower for smaller values of λ: as λ approaches 0, firms will never find it profitable to lower wages below w_R. As a simple illustration, Figure 1 shows the relationship between realizations of θ and labor market outcomes for the case of $\lambda \approx 0$.

[11]Note that these two conditions imply that θ_R is the value of θ for which w_R is the equilibrium wage in the benchmark case: $w^*\left(\theta_R, p\right) = w_R$.

2.4 Impact of Increases in the Reference Wage

The above analysis implies that increases in the reference wage will expand the range of θ-values at which distortions occur. In addition, if λ is small so that wage cuts below the reference wage are rare, then reference wage increases will be particularly distortionary.[12]

Proposition 3: Distortions from reference wage increases

Suppose the reference wage increases to $w_S > w_R$. For any $\theta < \theta_S$ and λ sufficiently small:

$$\overline{w}(w_S, \theta, p) > \overline{w}(w_R, \theta, p)$$
$$\overline{L}(w_S, \theta, p) < \overline{L}(w_R, \theta, p).$$

Proof: See Appendix A. ■

Since $\theta_R < \theta_S$, the wage distortions for $\theta \leq \theta_R$ will now be larger under w_S than they were under w_R. This will cause a particularly large excess supply of labor for $\theta \leq \theta_R$: labor demand will now be lower (leading to a drop in employment) while labor supply will actually be higher due to the wage increase. Figure 2 illustrates the impact of a reference wage increase on labor market outcomes for the case of $\lambda \approx 0$.

2.5 Impact of Inflation

In the benchmark case, prices are neutral. It is straightforward to verify from conditions (5) and (6):

$$\frac{\partial w^*(\theta, p)}{p} = \frac{w^*}{p}$$

$$\frac{\partial L^*(\theta, p)}{p} = 0.$$

Firms raise nominal wages to exactly offset the change in real wages from a price increase, keeping real wages constant and employment at the same level.

[12] In the empirical work, reference wage increases will arise from transitory positive shocks in the previous year—which raise the wage in the previous year and therefore lead to a higher reference wage in the current year.

In contrast, when workers have fairness preferences over a nominal wage, inflation will no longer be neutral. When price levels rise, a given real wage level is associated with a higher nominal wage. As a result, for any w_R, a price increase means that the value of θ at which w_R is the market clearing nominal wage will now be lower. The rigidity will bind to the left of this lower θ value; this means distortions will affect a smaller portion of the θ-distribution.

Proposition 4: Inflation will mitigate distortions from nominal rigidity

For any fixed $\theta = \widetilde{\theta}$ *and* $p = \widetilde{p}$ *such that:*

$$\overline{w}\left(w_R, \widetilde{\theta}, \widetilde{p}\right) = w_R \text{ and } J\overline{L}\left(w_R, \widetilde{\theta}, \widetilde{p}\right) < \frac{1}{\phi} u\left(\frac{\overline{w}\left(w_R, \widetilde{\theta}, \tilde{p}\right)}{p}\right),$$

$\exists p' > \widetilde{p}$ such that $\forall p \geq p'$:

$$\overline{w}\left(w_R, \widetilde{\theta}, p\right) = w^*\left(\widetilde{\theta}, p\right) \text{ and } J\overline{L}\left(w_R, \widetilde{\theta}, p\right) = \frac{1}{\phi} u\left(\frac{\overline{w}\left(w_R, \widetilde{\theta}, p\right)}{p}\right)$$

Proof: See Appendix A. ■

For any fixed $\widetilde{\theta}$ at which the nominal rigidity binds (i.e. the wage is at the reference wage and there is excess supply), a sufficiently large increase in prices will lead to nominal wages rising above the reference wage. This will enable real wages to fall without incurring effort retaliation from workers. The wage at $\widetilde{\theta}$ will correspond to the benchmark case and the labor market will clear.

Figure 3 illustrates how inflation moderates the distortions described in Propositions 2 and 3 for the case of $\lambda \approx 0$. By Proposition 2, at a fixed $\widetilde{p}$, there will be a θ^A around which adjustment will be asymmetric. For $p > \widetilde{p}$, the wage outcomes for θ-values just below θ^A will adjust so that: $w^*(\theta, p) = \overline{w}(w_R, \theta, p) < \overline{w}\left(w_R, \theta^A, p\right) = w^*\left(\theta^A, p\right)$. In other words, inflation will lead to symmetric adjustment around θ^A. In addition, inflation can also offset distortions from reference wage increases (Proposition 3). For any set of reference wages w_R and w_S, at a given $\widetilde{\theta}$, a sufficiently high p will cause nominal wages to be above w_S. Then, whether the reference wage is w_R or w_S will clearly have no impact on the equilibrium wage, which will correspond to the benchmark.

3 Empirical Strategy

3.1 Context: Rural Labor Markets in India

Agricultural production in India, as in most developing countries, is largely undertaken on small-holder farms. The median farm size is 1 acre, with considerable variation in landholdings.[13] The composition of farm employment varies and is often a mix of household and hired labor. Markets for hired labor are active: most households buy and/or sell labor.[14] Workers are typically hired for standard tasks such as plowing, sowing, weeding, and harvesting.

The vast majority of hired labor is traded in decentralized markets for casual daily workers. For example, 97% of agricultural wage contracts are reported as casual wage contracts. In addition, 67% of landless rural workers report casual employment as their primary source of earnings.

There are few institutional constraints in these markets. Contracts are usually negotiated bilaterally between landowners and laborers in a decentralized manner; unions or other formal labor institutions are rare. Wage contracts are typically of short duration (on the order of days).[15] As a result, they can more easily reflect recent changes in market conditions and time worked is more flexible than in other contexts. Minimum wage policies are in practice ignored and there is little government intervention in the labor market (Rosenzweig 1980; 1988).

Agricultural production is heavily rainfall dependent and exhibits considerable seasonality in work intensity. The major rainfall episode is the yearly monsoon. The monsoon typically arrives between June-July in most parts of the country and marks the beginning of the agricultural year. For rice (the major crop in India) as well as some other crops, this is when field preparation and planting occur. The subsequent months involve various maintenance activities such as fertilizer application and weeding. Rice harvesting typically occurs between November and January, followed by post-harvest activities such as threshing and processing. March-May is the lean season. As discussed in Section 3.4, the monsoon affects labor demand in the various seasons over the agricultural year through impacts on planting levels, harvest yields, and the intensity of post-harvest tasks.

[13] This, along with the remaining statistics in this sub-section, are from India's National Sample Survey data (1982-2008), described in Section 3.3 below.

[14] See, for example, Table I of Rosenzweig (1980) for evidence from India, Tables I-III in Benjamin (1992) for evidence from Indonesia, and Bardhan (1997) for a broader discussion of the composition of agricultural employment.

[15] Of course, this does not rule out longer-term informal implicit contracts.

3.2 Empirical Tests

Testing the model's predictions requires identifying variation in both total factor productivity, θ, and in the nominal reference wage, w_R. I exploit rainfall variation to isolate shifters of both parameters in rural labor markets. A distinct labor market is defined as an Indian district (an administrative geographic unit). The empirical implementation will focus on discrete rainfall shocks: in each year, a labor market can experience a positive shock, no shock, or a negative shock (corresponding to a high, medium, or low realization of θ, respectively). These shocks have no persistent productivity impacts: the value of θ in each year is determined solely by the rainfall shock in that year.[16] In addition, I assume the reference wage in a season equals the average market wage during that season in the previous year. A positive shock in the previous year would on average have raised wages in each season in the previous year, leading to a higher reference wage in each season this year.

This implies that examining the joint impact of lagged and current shocks on current wages can be used to test the model's predictions. Since there are 3 possible shocks in a given year, over every consecutive 2-year period, there are 9 possible realizations of shocks. This gives rise to the following estimating equation for wages:

$$\begin{aligned} w_{idst} \;=\;& \alpha_0^i + \alpha_0^{ii} S_{dt}^{\{-,0\}} + \alpha_1^i S_{dt}^{\{0,+\}} + \alpha_1^{ii} S_{dt}^{\{-,+\}} + \alpha_1^{iii} S_{dt}^{\{+,+\}} + \alpha_2^i S_{dt}^{\{0,-\}} + \alpha_2^{ii} S_{dt}^{\{-,-\}} \\ &+ \alpha_3^i S_{dt}^{\{+,-\}} + \alpha_3^{ii} S_{dt}^{\{+,0\}} + \varphi \mathbf{X_{idst}} + \psi_{\mathbf{d}} + \eta_{\mathbf{t}} + \tau_{\mathbf{s}} + \varepsilon_{idst}, \end{aligned} \tag{9}$$

where w_{idst} is the nominal wage of worker i in district d in season s of year t; X_{idst} is a vector of controls; $\psi_{\mathbf{d}}$, $\eta_{\mathbf{t}}$, and $\tau_{\mathbf{s}}$ are vectors of district, year, and season fixed effects, respectively.

Each of the remaining 8 covariates is an indicator for the realization of a particular sequence of shocks. The indicators take the form $S_{dt}^{\{i,j\}}$, where i denotes district d's shock in year $t-1$ and j denotes the district's shock in year t. The i and j take the values $-$, 0, and $+$, which correspond to the realization of a negative shock, no shock, and a positive shock, respectively. Each indicator equals 1 if that particular sequence of shocks was realized and equals 0 otherwise. For example $S_{dt}^{\{+,0\}}$, equals 1 if district d had a positive shock last year and no shock this year, and equals 0 otherwise. The sequence $S_{dt}^{\{0,0\}}$, which is the case when the district experienced no shock last year

[16] This is a standard assumption in prior work that exploits rainfall shocks to investigate a range of outcomes in India (e.g., Paxson 1992; Rosenzweig and Wolpin 1993; Townsend 1994; Jayachandran 2006). In Section 5, I use the results to rule out persistent productivity impacts of shocks.

and no shock this year, is omitted and serves as the reference case. Shocks are drawn from an iid distribution each year and are uncorrelated with the residual error, ε_{idst}. Thus, each of the coefficients on the indicator functions in equation (9) represents the reduced form average effect of that particular sequence of shocks on year t wages relative to $S_{dt}^{\{0,0\}}$.

Proposition 2 of the model predicts asymmetric adjustment in wages.

Prediction 1: Wage distortions: negative shocks

If there is no rigidity, wages will fall in response to negative shocks. In the presence of downward rigidities, wages may not fall in response to negative shocks.

I test this prediction by checking whether wages fall in response to contemporaneous negative shocks—the sequences $S_{dt}^{\{0,-\}}$, $S_{dt}^{\{-,-\}}$, and $S_{dt}^{\{+,-\}}$—relative to the reference case of $S_{dt}^{\{0,0\}}$. Note that in the presence of downward rigidities, $S_{dt}^{\{+,-\}}$ may cause wages to be even higher than the reference case, as discussed in Prediction 2 below.

Test 1:

$H_0 : \alpha_2^i < 0$, $\alpha_2^{ii} < 0$, and $\alpha_3^i < 0$.

$H_1 : \alpha_2^i = \alpha_2^{ii} = 0$ and $\alpha_3^i \geq 0$ under sufficiently severe downward rigidities.

Under the null of no rigidities, only current shocks should predict wages: for $S_{dt}^{\{i,j\}}$, the sign of the coefficient should be determined solely by j. However, under rigidities, lagged shocks can matter through their impact on the current reference wage (Proposition 3).

Prediction 2: Wage distortions: lagged positive shocks

If there is no rigidity, lagged positive shocks will have no impact on current wages. In the presence of downward rigidities, when a positive shock last year is followed by a non-positive shock this year, this may lead to higher current wages than if the lagged positive shock had not occurred.

I test this by checking whether the sequences $S_{dt}^{\{+,-\}}$ and $S_{dt}^{\{+,0\}}$ raise wages relative to the reference case of $S_{dt}^{\{0,0\}}$.

Test 2:

$H_0 : \alpha_3^i < 0$ and $\alpha_3^{ii} = 0$.

$H_1 : \alpha_3^i > 0$ and $\alpha_3^{ii} > 0$ under sufficiently severe downward rigidities.

Note that Tests 1 and 2 only have power under sufficiently large costs of worker retaliation (i.e. sufficiently small λ). If this cost is sufficiently low, firms will cut wages in response to decreases in θ and this estimation strategy may fail to produce a rejection of the null even though rigidities exist.

The remaining sequences of shocks in model (9) do not distinguish downward nominal rigidity from the benchmark case—they will have the same effects on wages in both cases. Specifically, when a negative shock is followed by no shock, wages should be the same as in the reference case: $\alpha_0^{ii} = 0$. In addition, contemporaneous positive shocks will increase wages relative to the reference case: $\alpha_1^i > 0$, $\alpha_1^{ii} > 0$, and $\alpha_1^{iii} > 0$. These sequences are included for completeness in the estimating equations.

To simplify the empirical analysis, the below alternate specification combines sequences of shocks into groups with common predictions:

$$\begin{aligned} w_{idst} \quad = \quad & \beta_0 + \beta_1 \left[S_{dt}^{\{0,+\}} + S_{dt}^{\{-,+\}} + S_{dt}^{\{+,+\}} \right] + \beta_2 \left[S_{dt}^{\{0,-\}} + S_{dt}^{\{-,-\}} \right] + \beta_3^i S_{dt}^{\{+,-\}} + \beta_3^{ii} S_{dt}^{\{+,0\}} \\ & + \varphi \mathbf{X_{idst}} + \psi_{\mathbf{d}} + \eta_{\mathbf{t}} + \tau_{\mathbf{s}} + \varepsilon_{idst}. \end{aligned} \tag{10}$$

The omitted category in model (10) is the sequences $S_{dt}^{\{0,0\}}$ and $S_{dt}^{\{-,0\}}$. Each term in brackets constitutes a new indicator function: $\left[S_{dt}^{\{0,+\}} + S_{dt}^{\{-,+\}} + S_{dt}^{\{+,+\}} \right]$ equals 1 if district d experienced a contemporaneous positive shock in year t and equals 0 otherwise, and $\left[S_{dt}^{\{0,-\}} + S_{dt}^{\{-,-\}} \right]$ equals 1 if the district had a non-positive shock last year followed by a negative shock this year. All other covariates are the same as in (9). Tests 1 and 2 imply that under sufficiently severe rigidities, $\beta_2 = 0$, $\beta_3^i > 0$, and $\beta_3^{ii} > 0$.

In the presence of rigidities, inflation will enable symmetric wage adjustment and moderate the effects of reference wage increases (Proposition 4):

Prediction 3: Impact of inflation on wage distortions

In the absence of rigidities, inflation will not alter the impact of shocks. In the presence of rigidities, when inflation is higher, wages will be more likely to be lower during negative *shocks. In addition, when inflation is higher, lagged positive shocks will be less likely to raise current wages.*

The following regression model adds interactions of each of the shock categories with the inflation rate:

$$\begin{aligned} w_{idst} \;=\; & \gamma_0 \,+\, \gamma_1 \left[S_{dt}^{\{0,+\}} + S_{dt}^{\{-,+\}} + S_{dt}^{\{+,+\}}\right] \,+\, \delta_1 I_{dt} \left[S_{dt}^{\{0,+\}} + S_{dt}^{\{-,+\}} + S_{dt}^{\{+,+\}}\right] \\ & + \gamma_2 \left[S_{dt}^{\{0,-\}} + S_{dt}^{\{-,-\}}\right] \,+\, \delta_2 I_{dt} \left[S_{dt}^{\{0,-\}} + S_{dt}^{\{-,-\}}\right] \\ & + \gamma_3^i S_{dt}^{\{+,-\}} \,+\, \gamma_3^{ii} S_{dt}^{\{+,0\}} \,+\, \delta_3^i I_{dt} S_{dt}^{\{+,-\}} \,+\, \delta_3^{ii} I_{dt} S_{dt}^{\{+,0\}} \\ & + \varphi \mathbf{X_{idst}} + \psi_{\mathbf{d}} \,+\, \eta_{\mathbf{t}} + \tau_{\mathbf{s}} + \varepsilon_{idst}, \end{aligned} \tag{11}$$

where I_{dt} is the percentage change in price levels in district d between years $t-1$ and t.

Test 3:

$H_0 : \delta_1 = \delta_2 = \delta_3^i = \delta_3^{ii} = 0$

$H_1 : \delta_1 = 0$, while $\delta_2 < 0$, $\delta_3^i < 0$, and $\delta_3^{ii} < 0$.

In the reference case, employers will raise nominal wages by the inflation rate to keep real wages constant. In cases where rigidities cause wage distortions—contemporaneous negative shocks and lagged positive shocks—employers can simply not adjust nominal wages upward, thereby achieving real wage reductions. As a result, when inflation is higher, nominal wages will be more likely to be lower in these cases relative to the reference case.

For a given non-positive shock in the current year, a transitory positive shock in the previous year raises current wages without affecting the current value of θ. This wage distortion should generate a distortion on employment:

Prediction 4: Employment distortions: lagged positive shocks

If there is no rigidity, lagged positive shocks will have no impact on current employment. In the presence of downward rigidities, when a positive shock last year is followed by a non-positive shock this year, this will lead to lower employment than if the lagged positive shock had not occurred.

The following model allows for tests for the impact of shocks on employment:

$$
\begin{aligned}
e_{idst} \;=\; & \rho_0 + \rho_1\left[S_{dt}^{\{0,+\}} + \rho_{dt}^{\{-,+\}} + \rho_{dt}^{\{+,+\}}\right] + \rho_2\left[S_{dt}^{\{0,-\}} + S_{dt}^{\{-,-\}}\right] + \rho_3^i S_{dt}^{\{+,-\}} + \rho_3^{ii} S_{dt}^{\{+,0\}} \\
& + \varphi \mathbf{X_{idst}} + \psi_{\mathbf{d}} + \eta_{\mathbf{t}} + \tau_{\mathbf{s}} + \varepsilon_{idst},
\end{aligned} \tag{12}
$$

where e_{idst} is the employment level of worker i in district d in season s of year t, and all other covariates are the same as in model (10). As tests of Prediction 4, sequences $S_{dt}^{\{0,0\}}$ and $S_{dt}^{\{-,0\}}$ (which are the omitted category) serve as counterfactuals for $S_{dt}^{\{+,0\}}$—the value of θ is the same in the current year, the only difference is whether there is a wage distortion from a lagged positive shock. Similarly, $S_{dt}^{\{0,-\}}$ and $S_{dt}^{\{-,-\}}$ serve as counterfactuals for $S_{dt}^{\{+,-\}}$—while employment should fall under all these sequences, the fall should be relatively more severe for $S_{dt}^{\{+,-\}}$ due to the added wage distortion from the lagged positive shock.[17]

Test 4:

$H_0 : \rho_3^i = \rho_2 < 0$ and $\rho_3^{ii} = 0$

$H_1 : \rho_3^i < \rho_2 < 0$ and $\rho_3^{ii} < 0$.

In villages, those who own land have the option to exhaust their own labor supply on their farms before hiring external non-household labor. In contrast, the landless must sell their labor externally to other farms at the prevailing wage. As a result, when nominal rigidities bind, those with less land will be most likely to be rationed out of the labor market.

Prediction 4A: Employment distortions will be more severe for those with less land

Those with less land will be relatively more likely to suffer employment losses after lagged positive shocks.

This prediction is readily tested by adding interactions of land size with the shock categories in

[17] The model predicts employment distortions from all contemporaneous negative shocks. However, testing for distortions under the sequences $S_{dt}^{\{0,-\}}$ and $S_{dt}^{\{0,-\}}$ requires a counterfactual benchmark of how much employment would have fallen if wages were flexible. However, there is no clear benchmark for this; constructing one would require imposing assumptions about the parameters of the production function and labor supply elasticity. Consequently, I focus in the employment tests on the effect of lag positive shocks, which have clear counterfactuals with clean qualitative predictions.

regression model (12) and checking if the distortions from $S_{dt}^{\{+,-\}}$ and $S_{dt}^{\{+,0\}}$ are higher for those with less land.

3.3 Data

Wage and employment data for over 500 Indian districts during the years 1956-2008 is constructed using two primary datasets.

The first source is the rural sample of the Employment/Unemployment rounds of the Indian National Sample Survey, a nationally representative survey of over 500 Indian districts.[18] Households in each district are sampled on a rolling basis over the agricultural year (July to June). The agricultural years 1982, 1983, 1987, 1993, 1999, 2004, 2005, and 2007 are covered. The survey elicits daily employment and wage information for each household member over the 7 days preceding the interview. I compute the daily agricultural wage as paid earnings for casual agricultural work divided by days worked.[19] I measure agricultural employment as the total percentage of the interview reference period during which a worker was employed in agricultural activities (own farm work plus hired out labor). This employment variable is constructed for members of the agricultural labor force (i.e. individuals who report agriculture as their primary or subsidiary source of employment).

The second source is the World Bank Agriculture and Climate dataset, which provides yearly panel data on 228 Indian districts in 13 states over the agricultural years 1956-1987.[20] The unit of observation is a district-year. The reported wage variable equals the mean daily wage for a male ploughman in the district-year.[21] Data on 20 crops, including acres planted and yields, is also included.

Rainfall data is taken from *Terrestrial Precipitation: 1900-2008 Gridded Monthly Time Series*

[18] A district is an administrative unit in India, with an average of 17 districts per state. Like counties in the US, districts vary greatly in size. On average, a district has approximately 2 million total residents.

[19] Agricultural work is identified in the questionnaire as work activity corresponding to one of 6 possible agricultural operations such as plowing, sowing, weeding, etc. The wage data is restricted to observations in which a worker was paid for work performed; these do not include imputed wages for self-employment. I use total wage earnings: cash plus in-kind wages. 93% of wage observations in the sample have some cash component. Given potential measurement error in the valuation of in-kind wages, as a robustness check, I have also performed the analysis using log cash wages as the dependent variable in the wage regressions. The results are similar.

[20] The dataset includes data on 271 districts. I limit analysis to 228 agricultural districts, which I define as the districts whose mean percentage of land area planted with rice in the sample is at least 1%. Since rice is the dominant crop in India, districts that do not grow any rice are unlikely to engage in substantial agricultural activity. Performing the analysis below with all 271 districts gives similar results, with slightly larger standard errors.

[21] This information was collected from sampled villages within each district. A knowledgeable person in each village, such as a school teacher or village official, was asked the prevailing wage rate in the village. In years when the data for a male ploughman are not available, wages for a general male agricultural laborer are used instead.

(version 2.01), constructed by the Center for Climatic Research, University of Delaware. Rainfall estimates are constructed for 0.5 by 0.5 degree latitude-longitude grids by interpolating from 20 nearby weather stations. I match the geographic center of each district to the nearest latitude-longitude node in the rain data. These district coordinates are included in the World Bank data; for the NSS data, I have obtained them using district boundaries from the Indian census. The measure of interest is rainfall in the first month when the monsoon typically arrives in a district, which ranges from May to July for each district. Rainfall shock definitions, discussed below, are constructed as deviations from the district's usual rainfall in the sample. Rainfall distributions are computed for each district separately for each dataset: they are based on the years 1956-1987 for the World Bank wage data and the years 1982-2007 for the NSS data.

The national inflation rate is constructed from CPI indices from the government publication *Agricultural Prices in India*. Inflation in year t is defined as the average change in monthly inflation from July of year t-1 to June of year t. For 1965-1987, this is computed as the mean inflation level across all states using the state CPI for Agricultural Workers. For 1956-1962, it is computed from the national Working Class Cost of Living Index, since agricultural CPI numbers are not available for these earlier years. There is no inflation data available for 4 of the years in the World Bank data: 1960, 1963, 1964, and 1975.

Table 1 provides summary statistics for the key variables used in the analysis.

3.4 Definition of Shocks

Figure 4 shows the non-parametric relationship between rainfall levels and 3 outcomes: crop yields, agricultural employment, and agricultural wages. The yield and wage graphs use observations from the World Bank data. The employment results are from the NSS data since the World Bank dataset does not contain employment information. I regress each dependent variable on controls (including year and district fixed effects) and rainfall decile dummies.[22] Each decile dummy is an indicator for whether the district's rainfall in the first month of the monsoon that year fell within the given

[22] District identifiers are not available for the first three rounds of the NSS data. For these years, the smallest geographic identifier is the region—there are on average 2.6 regions per state in the NSS data, and a region is comprised of 8 districts on average. As a result, for all regressions using the NSS dataset, the geographic fixed effects are region fixed effects for the first three rounds and district fixed effects for the remaining rounds. This is equivalent to using two pooled panels with separate fixed effects for analysis. Using a common set of region fixed effects for all rounds gives similar (though slightly less precise) results in the regressions.

decile of the district's rain distribution. The graphs plot the coefficients for the decile dummies.

Figure 4 indicates that on average, high rainfall levels are associated with increased crop yields, higher agricultural employment, and wage increases. Note that even rainfall in the uppermost decile is a positive productivity shock. In contrast, low rainfall levels (droughts) are associated with lower average yields and employment; there is weak evidence that wages are lower. In the wage regression shown in Panel C, the F-test for joint significance of the ninth and tenth decile coefficients has a p-value of 0.066, while the F-test for the first and second deciles has a p-value of 0.357.

Panels A and B are consistent with the presumption that high (low) rainfall levels constitute positive (negative) shocks to the marginal product of labor and increase (decrease) labor demand. I create discrete categories for positive and negative shocks to reflect the non-linear effects of rainfall on productivity and to increase statistical power. A positive demand shock is defined as rainfall above the eightieth percentile for the district; a drought as rainfall below the twentieth percentile; and no shock as rainfall between the twentieth and eightieth percentiles.[23] Jayachandran (2006) also uses rainfall to identify labor demand shifts and employs the same percentile cutoffs in defining shocks. Table 1 provides summary statistics on rainfall shocks in the sample.

Rainfall is serially uncorrelated. I verify this in Appendix Table 1. To allow for the possibility that shocks across districts may be correlated within a given year, standard errors are clustered by region-year in all regressions, using the region definitions provided in the NSS data.[24]

While shocks occur at the start of the agricultural year, the empirical approach assumes their impact persists over the entire year. Appendix Table 2 examines differential impacts over calendar quarters. The variation in employment levels across quarters attests to the substantial seasonality in agriculture. However, I cannot reject that the impact of shocks on wages and employment is the same across quarters. As a result, in the analysis that follows, I pool observations within each agricultural year and examine mean impacts of shocks over the entire year.

[23]Although the cut-offs are symmetric, this does not presume that the magnitude of shocks from the upper and lower tails of the rainfall distribution is symmetric.

[24]Appendix Table 1 provides some evidence for negative serial correlation in rainfall. Clustering standard errors by region makes minor difference in the results, and slightly improves precision in some cases. To be conservative, I cluster by region-year.

4 Results

4.1 Distributions of Wage Changes

Before moving to the main empirical tests, I examine the distribution of wage changes for evidence of wage stickiness.

Figure 5 displays histograms of year-to-year percentage wage changes in the World Bank panel. Panel A shows the distribution of nominal wage changes. The figure shows a bunching of mass to the right of nominal zero, with a discontinuous drop to the left of zero. 17 percent of observations are zero nominal changes. Since the district wage data is computed by averaging wages from sampled villages, this likely underestimates the percentage of zero changes in the underlying micro-data. In an economy experiencing a continuous distribution of shocks (from rainfall or other events) to the marginal product of labor, one would not expect a large discrete jump at zero in the absence of nominal rigidities (Kahn 1994; McLaughlin 1994). Consequently, this figure provides prima facie evidence for nominal rigidity. However, an important concern with this approach is measurement error in reported wages. If wages are reported in round increments (while actual wages vary continuously) or there is recall bias in reporting, this would make observing nominal zero changes more likely.

Panel B displays the distribution of real wage changes, using the local state CPI to compute real wages. Only 0.07% of observations are zero real wage changes. In addition, the mass is distributed fairly smoothly to the left and right of zero. There is little evidence of real wage rigidity.

Panels C-D examine whether real wage cuts are more likely when inflation is higher. I define high inflation years state inflation above 6% (slightly below the sample median). Both panels use observations in which real wage cuts should be especially likely. The histograms in Panel C limit observations to district-years with contemporaneous droughts. Only 29% of observations are real wage cuts in low inflation years, contrasted with 64% of observations in high inflation years.[25] The histograms in Panel D limit observations to district-years in which the district experienced a positive shock in the previous year, which would have caused an increase in wages in the previous year. Since

[25] Of course, not all districts would be expected to cut wages since rainfall shocks are not the only determinants of labor productivity. Indian agriculture has gone through periods of strong national and localized growth—for example, from the adoption of green revolution technologies or infrastructure investments. Rainfall shocks are uncorrelated with these developments. Real wage increases are therefore expected even in the presence of negative rainfall shocks.

shocks are serially uncorrelated, these districts would on average have experienced a productivity decrease in the current year. Real wages should therefore be likely to fall. Again, the histograms show that real wage cuts are considerably more likely in high inflation years (67% of observations) than in low inflation years (30% of observations).

4.2 Tests for Wage Distortions

I now turn to the empirical strategy outlined in Section (3.2). Table 2 tests for wage distortions from rigidities. The dependent variable is the log of the nominal daily wage for agricultural work. Columns (1)-(3) show results from the World Bank district data, covering the years 1956-1987. Columns (4)-(6) shows results from the NSS individual data, covering the years 1982-2008. Columns (1) and (4) provide estimates of regression model (9).[26] The results are qualitatively similar in both columns. As expected under both rigidity and flexible wage models, the coefficient on the sequence $S_{dt}^{\{-,0\}}$ (row 2) is indistinguishable from zero and contemporaneous positive shocks (rows 3-5) raise wages. For example, a zero shock last year followed by a positive shock this year increases wages by approximately 2.1% in the World Bank data and 4.5% in the NSS data.

The coefficients on $S_{dt}^{\{0,-\}}$, $S_{dt}^{\{-,-\}}$, and $S_{dt}^{\{+,-\}}$ (rows 6-8) estimate the impact of contemporaneous droughts (Test 1). Consistent with downward rigidity, there is little evidence of wage decreases under droughts in both datasets. While the $S_{dt}^{\{0,-\}}$ and $S_{dt}^{\{-,-\}}$ coefficients have a negative sign, they are generally small in magnitude and I cannot reject they are zero; the $S_{dt}^{\{+,-\}}$ coefficient is actually positive.

Finally, the coefficients on $S_{dt}^{\{+,-\}}$ and $S_{dt}^{\{+,0\}}$ (rows 8-9) test for persistent effects of lag positive shocks (Test 2). In the World Bank data, when there is a positive shock last year and no shock this year, wages are 2.1% higher on average than if last year's positive shock had not occurred (significant at the 5% level). Even in the more extreme case when a positive shock is followed by a drought, wages are 3.8% higher on average than if there had been no shocks in either period (significant at the 10% level). These results bear out in the NSS data as well: this year's wages are about 2.6% and 11.5% higher on average when a positive shock last year is followed by a zero shock

[26] There is a small change in the specification for the World Bank data. Since the unit of observation is a district-year, the dependent variable is w_{dt}, the log nominal wage in district d in year t, and there are no individual-level controls or season fixed effects.

or drought, respectively, this year.[27]

Columns (2) and (5) of Table 2 repeat this analysis for the simpler specification in regression model (10). The results are similar to the previous columns. Finally, columns (3) and (6) repeat this specification, but also collapse the sequences used for the lag positive shock tests ($S_{dt}^{\{+,-\}}$ and $S_{dt}^{\{+,0\}}$; rows 8-9) into one cell. The results in these columns indicate that in both datasets, wages are on average the same this year regardless of whether the positive shock occurred last year or this year.[28]

For simplicity, the main specification focuses on shocks in the current year and previous year only. Appendix Table 4 examines the duration of persistence of shocks. In the World Bank data—positive shocks raise nominal wages for up to 5 years. In the NSS data, they do not significantly impact wages for more than 1 future year on average. This is consistent with higher levels of real agricultural growth in India during the NSS data years. As expected, droughts have no persistent effects in either dataset. Note that focusing on only last year's shocks in the main specification makes a rejection in Test 2 (lag positive shocks) less likely—the main specification therefore enables simplicity without biasing the results towards finding rigidity.

4.3 Impact of Inflation on Wage Distortions

To test whether inflation moderates the wage distortions documented above, I use the World Bank data since it covers 32 years, providing substantial variation in inflation. Column (1) of Table 3 shows estimates of model (10) for the restricted sample for which inflation data is available for comparison purposes. The regressions in columns (2)-(3) add interactions of each of the shock categories with measures of the national inflation rate. In column (2), the measure is the continuous inflation rate–this corresponds to the specification in model (11). In column (3), the inflation measure is an indicator that equals 1 if the inflation rate is above 6% (slightly below the sample median) and

[27] This coefficient of 0.115, which measures the mean impact of a positive shock followed by a negative shock in the NSS data, is surprisingly large. However, this seems to be a result of sampling variation in the data. One cannot reject, for example, that this coefficient is the same as the measured impact of a negative shock followed by a positive shock in the NSS data.

[28] In Appendix Table 3, I use an alternate specification to test for the impact of shocks on wages in both datasets. Instead of the 9 discrete cells, I include dummies for positive shocks and droughts in current and previous periods, along with a full set of interactions between current and lagged shocks. The model offers 2 sets of predictions under the null of no rigidity. First, contemporaneous droughts should lead to wage decreases. As in Table 2, there is no support for this. Second, lag shocks should not predict current wages. The F-test p-values reported at the bottom of the table test this restriction for covariates involving lag positive shocks and also for covariates involving any lag shocks—these tests are significant at the 5% level or less in each case.

equals 0 otherwise. Consistent with Test 3, contemporaneous droughts and lag positive shocks are less likely to cause wage distortions when inflation is higher. For example, the results in column (3) indicate that when a non-positive shock is followed by a drought, wages are the same as the reference cell on average when the inflation rate is below 6% (row 3). In contrast, when inflation is above 6%, wages are 3.6% lower than the reference cell (row 4). The F-test for whether, under high inflation, wages are the same during droughts as the reference cell has a p-value of 0.027 (reported at the bottom of the table). Thus, wages are indeed lower under droughts when inflation is sufficiently high. Similarly, when inflation is low, lag positive shocks increase current nominal wages (rows 5 and 7). When inflation is high, lag positive shocks do not cause persistent effects on future wages (the interactions in rows 6 and 8 are negative). For example, when a positive shock is followed by no shock, I cannot reject that wages are the same as the reference cell when inflation is above 6% (p-value 0.678).

The regressions in columns (4)-(6) repeat this analysis, with one change in the definition of shocks. To exploit the fact that positive shocks persist over many years in the World Bank data, I define a lag positive shock as at least one positive shock anytime in the past 3 years.[29] The remaining shock definitions remain the same. This yields qualitatively similar results to the regressions in columns (1)-(3), but increases precision.

In Appendix Table 5, I rule out two sets of potential concerns. The first is that rainfall shocks may influence the inflation rate. Columns (1)-(2) show regressions of the national inflation rate on the shock categories (as defined in column (1) of Table 3). There is little correlation between shocks and inflation—the coefficients on contemporaneous droughts and lag positive shocks (rows 3, 5, and 7) are especially small and insignificant. As a further check, column (3) shows a regression of the log nominal wage on the shock categories and an interaction with inflation, where the inflation rate has been computed as the mean inflation rate across all states except the district's own state. This is a useful robustness check since a district's local rainfall is especially unlikely to be correlated with inflation in other states. The results are similar to those in Table 3, though are less significant since state-level inflation data is available for a limited number of years. The second concern is that there are co-trends in inflation and the impact of rainfall shocks. For example, if inflation and the

[29]The results are similar if other definitions for lag positive shocks are used instead, such as at least one shock in the past 2 years or 4 years.

adoption of irrigation (which makes crops less reliant on rainfall) both trend upward over time, this could create a spurious correlation. I check for such co-trends by interacting the shocks with a linear time trend in column (4) and a dummy for whether the year is after 1970 (the sample mid-point and the beginning of India's green revolution) in column (5). The interaction coefficients in both columns are extremely small and insignificant, indicating that the inflation results are not driven by co-trends.

4.4 Tests for Employment Distortions

To check for evidence of employment distortions, I begin by examining the impact of lagged positive shocks on the distribution of employment. Figure 6 compares kernel density estimates of mean employment in district-years with and without lagged positive shocks in the NSS data. The observations are limited to district-years in which there was no contemporaneous positive shock. Consistent with Prediction 4, lagged positive shocks cause the employment distribution to shift to the left. This provides initial evidence that downward rigidity reduces aggregate employment.

Table 4 provides statistical tests of employment distortions and quantifies their magnitude. The dependent variable is the number of worker-days in the last 7 days in which the worker was employed in agricultural work (own farm work plus hired out work). Panel A begins by examining the mean impact of lagged positive shocks on employment. Agricultural laborers and farmers experience an average decrease in employment of 0.111 days per week if their district experienced a positive shock in the previous year (relative to no positive shock in the previous year). This constitutes a 3% decrease in agricultural activity. Column (2) adds an interaction with a measure of landholding: acres per adult in the household. In the year after a positive shock, landless laborers experience a 6% decrease in employment (significant at the 1% level). In contrast, those with land are less likely to face rationing. Column (3) repeats the analysis in column (2) but excludes observations from the lean quarter (April-June), when there is limited agricultural activity; the results are quite similar.

Panel B examines employment effects using the full specification. Column (1) provides estimates of regression model (12). Contemporaneous positive shocks (row 1) raise average employment by 0.078 days per week, or 2.2 percent. Contemporaneous droughts—which did not lead to wage cuts—do decrease employment. The $S_{dt}^{\{0,-\}}$ and $S_{dt}^{\{-,-\}}$ sequences (row 3) reduce employment by 0.116 days; this constitutes a 3.3% reduction and is significant at the 5% level.

The coefficients in row 5 and 7 provide tests of Prediction 4. When a drought is preceded by a positive shock, employment drops by about 0.25 days per week (row 5). This magnitude is twice as large as the decrease that occurs when a drought is not preceded by a lag positive shock (row 3). In addition, when a lag positive shock is followed by no shock (row 7), the average worker experiences a drop in employment of about 0.107 days (or 3%) relative to the reference cell.[30]

The regression in column (2) add interactions of acres per adult with each of the shock categories. The results conform to Prediction 4A. When a positive shock last year is followed by a drought in the current year (sequence $S_{dt}^{\{+,-\}}$, row 5), landless laborers are predicted to experience an employment decrease of 0.352 days per week; this corresponds to 10% of the mean employment level (significant at 1%). This magnitude is significantly larger than the 0.112 day decrease that results from a drought that wasn't preceded by a positive shock last year (row 3). The F-test for equality of the two coefficients has a p-value of 0.002. Note that difference in these coefficients is 0.240—about twice as large as the magnitude of the baseline employment effect of a drought. As expected, these employment decreases are less severe for those with more land: each additional acre of land per household adult is associated with an increase in employment of 0.123 days per week. Similarly, when a positive shock last year is followed by no shock in the current year ($S_{dt}^{\{+,0\}}$, row 7), the employment of landless agricultural workers is 0.213 days lower than if there hadn't been a positive shock in the previous year. It constitutes a 7% employment reduction and is significant at the 5% level. Again, this effect is about twice as large as the decrease in employment under a drought. Also in this case, landholdings mitigate these adverse employment effects. Finally, column (3) excludes observations from the lean quarter; the results are quite similar to column (2), and slightly stronger.[31]

In Appendix Table 7, I investigate a potential concern with the interpretation of the employment results: the possibility that rainfall shocks alter the composition of the agricultural labor force. In the presence of compositional effects, the employment variable will not accurately estimate changes in aggregate employment levels. For example, if lag positive shocks cause in-migration, increasing

[30] Appendix Table 6 repeats this analysis, showing the impact of each of the 9 sequences of shocks on employment separately.

[31] While landholding is an important determinant of worker-days spent in agriculture, it does not impact the wage received by workers. When the log nominal daily agricultural wage is regressed on the covariates in the regression in Column (2) of Table 4, the coefficients on the landholding controls and interactions terms are all extremely small in magnitude (between 0.00-0.002) and insignificant. These results are consistent with the presence of a prevailing market wage, which is the same for all agricultural workers who sell their labor externally on the market.

the number of agricultural workers, the percentage of days worked by each worker could decrease even if the aggregate number of worker-days has gone up. Appendix Table 7 investigates two ways in which shocks could create compositional changes—through migration into the village and by altering the probability that respondents identify agriculture as their occupation. There is little evidence that lag positive shocks influence either of these outcomes.[32]

4.5 Separation Failures Test: Compositional Effects on Household Employment

When employment is rationed, the household's labor supply decision will no longer be separable from its decision of how much labor to use on its farm. Households with less land, who cannot find external employment when rigidities bind, will supply more intensively to their own farms. Table 5 provides a test of this prediction. It decomposes total household agricultural employment into worker-days in the external labor market (as a paid agricultural labor) and worker-days on the household's own farm.

Panel A begins by examining the average impact of lagged positive shocks by landholding. Households are defined as having small, medium, and large landholdings, corresponding to the the lower, middle, and upper terciles of the sample distribution of acres per adult in the household, respectively. The sample is limited to agricultural households with positive landholding. The dependent variable in column (1) is the total number of days spent by household members in external employment (as a hired agricultural laborer on someone else's farm). Consistent with the results in Table 4, households with small landholdings face reductions in external employment after lagged positive shocks, while households with medium and large landholdings do not.

Column (2) provides the key test of the separation failure prediction. The dependent variable is the number of days spent by household members on their own farm. In the year after a positive shock, households with small landholdings—who are rationed out of the external market—increase labor supply on their own farms by half a day a week on average. This is a 7% increase relative to the mean, and is about the same as how much these households increase own-farm production during a contemporaneous positive shock (see Panel B below). In contrast, own-farm labor supply does

[32]There is evidence that individuals are less likely to migrate into the village during contemporaneous droughts—in the main specification (Panel B), migration falls by 0.1%. However, the fact that the labor force is relatively smaller during droughts is unlikely to be the reason wages don't fall during these shocks. As a simple calibration, since the mean employment rate is 0.498, this can explain only a 0.001*0.498 = 0.000498 percentage point change in the number of worker-days.

not change after lagged positive shocks for medium-landholding households and actually decreases for large landowners (perhaps due to decreased supervision time in the field since less external labor is being hired). Column (3) shows the sum of off-farm and own-farm employment (the same dependent variable as in Table 4). Because households supplement decreased external employment with increases in own-farm work, there is little aggregate movement in total household employment after lagged positive shocks.

Panel B repeats this analysis using the full specification. Rows 7 and 10 provide the coefficients of primary interest. When a positive shock is followed by no shock (row 10), households with small landholdings experience an average decrease in external employment of 1.23 days per week. In these years, they increase their supply of labor to their own farm by 0.701 days, or 10% of mean own-farm labor supply. The impacts on households with medium and large landholdings (rows 11-12) are similar to the pattern shown in Panel A.

In addition, when a positive shock is followed by a drought (row 7), households with small farms do not decrease own-farm labor supply, despite the negative productivity shock–the coefficient is positive (though insignificant). However, I cannot reject that this coefficient is equal in magnitude to the effect of a non-positive shock followed by a drought (row 4).

As a whole, these results provide evidence that households respond to rationing by increasing labor supply on their own farms. However, a full test of whether rationing leads the marginal product of labor on small farms to be lower than that on large farms requires farm-level data on total labor inputs. Farms in the bottom tercile of the landholding distribution are quite small and unlikely to hire much labor, so own-farm employment is likely highly correlated with total farm labor use. However, if these farms do hire some external labor, then some of the increase in own-farm supply may be offsetting decreases in labor hired by the farm. Farm-level labor use data is needed for a more complete understanding of how rationing affects the allocation of labor across farms.

4.6 Heterogeneity in Wage Rigidity: Crop Variation

Districts exhibit substantial heterogeneity in the extent of rigidity. To test for heterogeneity, in the World Bank panel data, I regress the log nominal wage on the three main categories of shocks (contemporaneous positive shocks, contemporaneous droughts preceded by a non-positive shock, and lag positive shocks followed by a non-positive shock), year fixed effects, district fixed effects, and an interaction of each of the district dummies with the contemporaneous droughts indicator. This is the same specification as in column (3) of Table 2 plus the interaction terms. The coefficient on each interaction term provides an estimate of that district's mean wage change to a drought in the sample (relative to the omitted district). If the effect of droughts is the same across all districts, then the coefficients on the interactions should be 0. The F-test of joint significance of the interaction coefficients has a p-value of 0.000, indicating heterogeneity in the extent to which districts respond to droughts. Repeating this analysis by instead interacting each district dummy with the lag positive shock indicator also suggests heterogeneity in the extent to which lag positive shocks influence future wages (the F-test of joint significance of the interaction coefficients has a p-value of 0.000).

Districts in India differ substantially in crops grown. The World Bank dataset contains data on 20 crops, including the percentage of land area in each district-year planted with each crop. Five of these twenty crops—soybeans, sesame, rapseed/mustard, sunflowers, and sugarcane—are extremely sensitive to the amount of labor hired during harvest.[33] For example, if the first three are not harvested quickly upon reaching maturity, their pods burst, spilling their seeds onto the ground and leading to large output losses.[34] In these areas, price flexibility is particularly important because inefficient labor allocation will lead to especially large profit losses.

I investigate whether rigidities are lower in areas where the costs of rigidity are likely to be higher due to crop characteristics. Specifically, I test whether districts with a greater percentage of land area planted with labor-sensitive crops are more responsive to shocks. The crop sensitivity measures were constructed as follows. For each of the five crops, the percentage of land-area planted with the crop in each district-year was regressed on year fixed effects to remove national time trends. The

[33]These crops were identified in the following manner. A researcher with a background in agricultural extension work in India compiled a timeline of work activities for each of the 20 crops, along with identifying which activities were particularly important for output. This information was based on consultations with an expert at an agricultural research university and numerous field interviews with farmers. The researcher identified these 5 crops as extremely sensitive to timely labor inputs for the reasons listed below. He did not know how this information would be used and did not have access to the World Bank dataset.

[34]Similarly, sunflower seeds will fall to the ground when they become over-ripe. A bigger practical concern, however, is that birds are relentless in eating the seeds as soon as they reach maturity. This poses such a large threat that farmers in richer countries like the US cut sunflowers early and let the seeds ripen indoors, or cover each sunflower head with protective covering to protect it from birds. These practices are not often followed in India, where farming is less capital intensive. Harvesting sunflowers quickly is therefore important for output levels. The constraint on sugarcane is institutional. Each sugarcane mill in India is assigned a command area; all growers within that area are required by law to sell their crop to that mill. To manage supply chains, mills assign farmers a harvest date on which they are allowed to sell their output to the mill; output is not accepted on other dates. Therefore, farmers must ensure their crop is prepared for delivery to the mill on their assigned date.

residuals for each of the five regressions were then summed to give the total adjusted percentage of land planted with these crops in each district-year.

Table 6 shows results from OLS regressions of the log nominal wage on indicators for each shock category, interactions of each shock category with a measure of the district's crop sensitivity, and year and district fixed effects. The measure in column (1) is the running average of the adjusted percentage over the past 5 years in each district. The current year and previous year are omitted when computing means, to preclude any possibility that current or lag rainfall shocks influence the crop sensitivity measure (via effects on planting decisions). The regression in column (2) shows interactions with a binary version of this measure, which equals 1 if the district's running average over the last 5 years is above the sample median and 0 otherwise.

The results indicate that districts with more labor-sensitive crops are substantially more likely to cut wages in response to droughts (row 4). For example, during droughts, wages are about 4.5% less in districts in the upper half of the distribution in terms of land area planted. The F-test for whether, in these high crop sensitivity districts, wages are the same during droughts as the reference cell has a p-value of 0.001 (reported at the bottom of the table). In addition, I cannot reject that lag positive shocks have no persistent wage effects in these districts.

The regressions in columns (3)-(4) repeat this analysis, but the crop sensitivity measure is constructed by averaging the adjusted percentage over the entire sample for each district. As before, current year and previous year are omitted when computing means. This reflects the time-invariant proportion of land planted with sensitive crops in a district. Column (3) uses the continuous percentage measure, while column (4) uses a binary indicator that equals 1 if the percentage is above the sample median and 0 otherwise. The results are similar to those in columns (1)-(2).

One potential concern with the interpretation of these results is that rainfall shocks may impact the marginal product of labor more in high sensitivity districts—the results could stem from different productivity effects of shocks. Alternately, if workers in these different types of districts have different labor supply elasticities, this may alter the equilibrium wage response. However, wages in high and low sensitivity districts are equally responsive to contemporaneous positive shocks (rows 1-2). But the effects of positive shocks only carry over to future wages in low sensitivity districts. This should not be the case if the results are due to differences in productivity effects or labor supply elasticities.

As a whole, these results are consistent with less rigidity in areas where crops are more sensitive to labor inputs. However, this evidence is only suggestive since crop choice is endogenous. It may be more profitable for farmers to grow labor-sensitive crops in less rigid areas, which could influence their planting decisions.

5 Alternate Explanations

Could the results be explained by reasons other than downward nominal wage rigidity? In this section, I discuss potential alternate explanations. I focus on three sets of competing explanations: alternate models of equilibrium unemployment, the possibility that rainfall shocks have persistent effects in future periods, and measurement error.

Efficiency wage models with micro-foundations that do not involve nominal rigidities—such as moral hazard, screening, labor turnover, or nutrition—also predict that wages may remain above market clearing levels in equilibrium. However, these models do not predict rigid wages—they generally predict that wages will decrease when labor productivity declines. For example, none of these models can account for why wages would rise under a positive shock but then not come back down to their prior level once the shock has dissipated, or why this should be influenced by inflation. Similar arguments apply to search friction models that do not incorporate some degree of nominal rigidity.

The second set of concerns is that rainfall shocks are not actually transitory, but have future effects on the economy through channels other than wage rigidity. For example, one potential confound arises if positive shocks have persistent productivity effects in future years. If this is the case, then lag positive shocks could raise future wages because they positively impact the marginal product of labor in the next year. However, in this case, employment should also be higher in the following year, whereas the results indicate substantial employment decreases.

Alternately, inter-temporal substitution of labor could cause an increase in future wages and decrease in employment. However, such labor supply shifters are difficult to reconcile with the inflation results: it is not clear why any of these should be more likely when inflation is lower. These explanations are also inconsistent with the hetergeneity in the employment results by landholding. Reductions in external employment are especially likely for those with less land, and these households respond by *increasing* labor supply on their own farms. It is therefore unlikely that the wage dynamics are driven by a decrease in labor supply in the year after a positive shock. Similar arguments imply that factors such as income effects, migration, or capital investment are also not driving the empirical findings. In addition, such explanations do not account for why wages do not fall in response to droughts.

A third concern is that measurement error—driven for example, by rounding error—could make wages appear more sticky than they are. As discussed above, this is especially a concern when using histograms of wage changes to document rigidity. However, the empirical tests in this paper are less subject to biases from such errors. Specifically, measurement error will only confound the above results if it is correlated in a very particular way with the random rainfall shocks: the error must be more likely in years with negative shocks and in years after positive shocks than in other years. It is not clear why respondents should be differentially more likely to round wages in these two special cases. In addition, if the observed wage persistence associated with lag positive shocks was simply due to reporting errors, we should not observe real employment effects or variation caused by inflation.

6 Mechanisms: Survey Evidence on Fairness Norms

The presence of nominal rigidities in markets for casual daily labor is perhaps especially surprising given the lack of institutional constraints in these markets. This suggests that non-instutional mechanisms discussed in the literature—such fairness norms against wage cuts—may play a role in maintaining rigid wages. To explore the relevance of fairness considerations, I conducted a survey in 34 villages in the Indian states of Orissa and Madhya Pradesh. 396 respondents (196 agricultural laborers and 200 landed farmers) were interviewed. Following Kahneman, Knetsch, and Thaler (1986), I presented workers with scenarios about wage setting behavior and asked them to rate the actions described as “Very fair”, “Fair”, “Unfair”, or “Very unfair”. Table 7 presents the text of these scenarios and reports the percentage of respondents who viewed each scenario as “Very unfair” or “Unfair”. Any given respondent was asked only half the questions to prevent the survey from becoming tedious. Some questions involve paired scenarios, which alter the text of the scenario slightly (questions 1A/1B, 3A/3C, and 9A/9B in Table 7); for these questions, each respondent was asked only 1 version of the scenario.

The states of Orissa and Madhya Pradesh were chosen because they differ greatly in the type of crops grown and other area characteristics. Orissa is poorer with a greater emphasis on staple crops; rice is the dominant crop in the areas surveyed. In contrast, Madhya Pradesh is more affluent; a large portion of the districts in which surveys were conducted are dominated by soybean farming. As discussed in Section 4.6, soybean output is substantially more sensitive to the amount of labor hired than rice. The crop heterogeneity results suggest that if fairness norms affect wage setting behavior, norms may be weaker in areas where costs of rigidity are likely to be higher. To check for suggestive evidence along these lines, Table 7 also reports responses to each scenario separately for each state along with a test for whether whether the differences are significant.

Panel A of Table 7 establishes baseline norms relating to wage cuts in 2 sets of situations. Question 1 presents a scenario in which a farmer pays a worker Rs. 120 for a task, and then cuts the wage for future work after a factory closure increases local unemployment. 62% of respondents believed it was unfair for the farmer to rehire his old employee at a lower wage, and 55% felt it was unfair for the farmer to hire one of the newly unemployed workers at a lower wage. Note that respondents in Orissa were about 30 percentage points more likely to denote these actions as unfair than respondents in Madhya Pradesh; the t-tests for equality of the means is significant at the 1% level. In Question 2, 79% of respondents indicated that it was unfair for a farmer who was facing personal financial distress to cut the wage of his workers. These perceptions were the same in both states.

Panel B explores the extent to which fairness norms are anchored on the nominal wage rather than the real wage. Question 3 investigates whether respondents are less likely to view real wage cuts as unfair if they do not involve nominal cuts. Respondents were told that last year the prevailing wage was Rs. 100 and that this year real wages are cut by about 5% because a drought will lower yields. However, the 5% real wage cut is presented in three different ways. When the cut consists of a 5% nominal decrease in a period of no inflation, 64% of respondents think it unfair. When the cut consists of no change in the nominal wage during a period of 5% inflation, the percentage viewing it as unfair drops to 38%. Finally, when the cut results from a 5% nominal increase in a period of 10% inflation, only 9% of respondents viewed it as unfair. This pattern is strongly consistent with the idea that workers are averse to nominal (and not necessarily real) wage cuts. Such questions produce comparable responses in other contexts like the US and Canada (Kahneman, Knetsch, and Thaler 1986; Shafir, Diamond, and Tversky 1997). Note that again there is a substantial difference between the 2 states. 81% of Orissa respondents think the nominal wage cut is unfair, whereas 45% of Madhya Pradesh respondents deem it as unfair. In contrast, when real wage cuts do not involve a decrease in the nominal wage, responses from the two states are similar.

Question 4 provides further evidence for the relevance of the nominal wage. When a farmer who pays workers a nominal wage plus food reduces real wages by eliminating food, only 24% of respondents viewed this as unfair. This is sharply lower than the reactions to nominal wage cuts of comparable magnitude in Panel A.[35]

Panel C demonstrates that several wage setting behaviors that are associated with market clearing are at odds with expressed fairness norms. For example, 61% of respondents felt it would be unfair if, during a period of high unemployment, a farmer asks workers for their reservation wage and then offers a job to the worker with the lowest reservation wage (Question 5). Question 7 presents a scenario in which a farmer raises the wage during a period of high labor demand to attract enough workers, and then lowers it again in later weeks when demand is lower. 63% viewed such behavior as unfair. As above, these behaviors violate norms in Orissa much more so than in Madhya Pradesh.

Finally, Panel D investigates whether respondents think worker effort depends on fairness perceptions. Question 9 presents a scenario in which a farmer offers a job to a worker in financial distress. In one version of the question, the farmer offers the prevailing wage rate; this would uphold fairness norms and possibly also show benevolence given the laborer's distress. In another version, the farmer sets the wage below the prevailing wage; this strongly violates fairness norms (see Question 6). Among respondents who were told that the wage was set at the prevailing wage, 55% percent believed the worker would exert more effort than usual and only 1% believed he would exert less effort than usual. In sharp contrast, when told the wage was below the prevailing rate, only 6% believed the worker would exert extra effort while 40% believed the worker would exert less effort than usual. This indicates a belief that worker effort responds to violations of fairness norms. Responses to this question were not substantially different in the two states.

[35] The value of the food, expressed in the vernacular as high quality food during lunch and other bonuses, exceeds Rs. 10. The magnitude of the real wage cut in question 4 is therefore comparable or greater than the cuts in Panel A.

As further evidence along these lines, Table 8 tabulates responses from survey questions about respondents' views about their own behavior or those of their fellow villagers. For example, when laborers were asked whether they offer to work at a wage below the prevailing rate when they have difficulty finding work (Question 2), only 31% said yes while 47% said no. As before, the differences between Orissa and Madhya Pradesh are stark—76% of Orissa laborers said no while only 14% of Madhya Pradesh laborers said no. Question 3 presents a more extreme scenario—whether the worker would accept a wage cut if he had faced prolonged unemployment and was in urgent need of money. Only 38% of Orissa laborers said yes, while 79% of Madhya Pradesh laborers said yes.

Responses by landowning farmers are consistent with these views. The overwhelming majority state that they have not themselves ever hired a laborer at a wage below the prevailing wage (Question 4).[36] In addition, when farmers are asked if a worker in their village would accept a wage cut if he had faced prolonged unemployment and was in urgent need of money, only 39% say yes. This number is considerably larger for Madhya Pradesh (67%) than Orissa (14%).

Of course, responses to hypothetical scenarios may not reflect the actual actions people take when the stakes are real. However, given the strength of the pattern of results, this evidence lends support to the view that fairness norms are a plausible way in which rigid wages are maintained in village labor markets. In addition, the stark difference in results between Orissa and Madhya Pradesh is consistent with the findings in Table 6 that areas with crops that are more sensitive to the amount of labor hired have more flexible wages. They suggest that labor market norms may form, at least in part, endogenously in response to local conditions.

7 Conclusion

In addition to their broad implications for unemployment and business cycle dynamics, the presence of nominal rigidities in village labor markets has particular relevance for the study of developing country labor markets.

Such rigidities give rise to an additional route through which production volatility (e.g., rainfall shocks) can have adverse consequences for the poor. One focus in the development literature has

[36] For this question, concerns that farmers may not truthfully answer a question about their past hiring behavior are warranted. However, whether the answers are truthful reports of past behavior or are driven by a desire by respondents to show that they conform to norms, at the very least, the results speak to the strength of the norms against wage cuts.

been that shocks cause shifts in the production frontier, leading to volatility in income; this affects welfare because the poor have limited ability to smooth income across periods. In the presence of wage rigidity, volatility has an additional implication: production may often not be at the frontier because labor markets do not adjust to optimize fully in each period. As implied by the employment results, this means rigidities may lower the levels and increase the volatility of output and income—they may compound the adverse consequences of production volatility.

The fact that those with less land respond to rationing by increasing production on their own farms provides another channel through which rigidities impact efficiency and output. Specifically, it suggests the presence of separation failures in rural labor markets. This is consistent, for example, with the widely documented fact that smaller farms tend to use more labor per acre and have higher yields per acre. This suggests that the distribution of landholdings in poor countries does not have only distributional consequences—it can impact the allocation of labor use in production, and through it, aggregate output.

Finally, the survey results suggest that fairness norms against wage cuts are strong, but they also differ substantially across areas. It is unclear whether such fairness preferences are inherent features of utility or whether they arise endogenously—for example, in response to worker demand for wage stability. The implicit insurance literature has discussed this as a potential source of wage rigidities (see, e.g., Rosen 1985). Insurance demand may be especially relevant given the low income levels in poor countries. In decentralized markets where it is difficult to contract on real wages and explicit contracts are difficult to enforce, fairness norms around nominal wages could be a way to maintain stable real wages. However, it is unclear why workers should be willing to accept employment losses in exchange for wage stability. Ultimately, identifying the cause of nominal rigidities requires better understanding of these factors. Further exploration of fairness norms in labor markets and the underlying mechanisms that give rise to them is a promising direction for future research.

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Appendix A: Model Proofs

This appendix presents proofs of the model propositions in Section 2. Before proceeding, it is useful to specify an allocation mechanism by which workers are matched to firms. This is needed to formalize the impact of off-equilibium deviations on firm profits. I assume all firms simultaneously post a wage. Firms satisfy labor demand in descending order of posted wages. If multiple firms post the same wage, those firms proceed in random order. This ensures that the firms offering the highest wage receive priority in hiring. For simplicitly, I assume each firm hires the available workers with the lowest ϕ values that are willing to work for it. This maximizes gains from trade in the narrow sense that for a given wage offer, those workers that would benefit the most from employment (the lowest ϕ workers) are the ones that get the job.

Proof of Proposition 1: Market Clearing in Benchmark Case

First, I show that the market clearing condition must hold in the benchmark case.

(i) Suppose there is excess labor supply: $JL^* < \frac{1}{\phi}u\left(\frac{w^*}{p}\right)$. Then firm j can cut its wage to some $w^* - \epsilon$ and still hire L^* workers. To see this, define δ as the slack in the market: $\delta = JL^* - \frac{1}{\phi}u\left(\frac{w^*}{p}\right)$. At wage $w_j = w^* - \epsilon$, by the allocation mechanism defined above, the supply of workers available to j equals the mass of workers that would be willing to work for j minus the mass of workers employed by the other (higher-wage) firms:

$$L_j^{Avail} \quad = \quad max\left\{\frac{1}{\phi}u\left(\frac{w^*-\epsilon}{p}\right) - (J-1)L^* \ , \ 0\right\}$$

Firm j can cut wages by ϵ and still hire L^* workers as long as ϵ satisfies the following condition:

$$\begin{aligned}
& L^* \leq \frac{1}{\phi}u\left(\frac{w^*-\epsilon}{p}\right) - (J-1)L^* \\
\implies \; & \frac{1}{J}\left[\frac{1}{\phi}u\left(\frac{w^*}{p}\right) - \delta\right] \leq \frac{1}{\phi}u\left(\frac{w^*-\epsilon}{p}\right) - \frac{J-1}{J}\left[\frac{1}{\phi}u\left(\frac{w^*}{p}\right) - \delta\right] \\
\implies \; & \frac{1}{\phi}u\left(\frac{w^*}{p}\right) - \delta \leq \frac{1}{\phi}u\left(\frac{w^*-\epsilon}{p}\right).
\end{aligned}$$

Such a wage cut will strictly decrease j's wage bill while holding revenue constant, thereby strictly increasing profits. Thus, there cannot be excess labor supply.

(ii) Suppose there is excess labor demand: $JL^* > \frac{1}{\phi}u\left(\frac{w^*}{p}\right)$. This implies that each firm is hiring strictly less labor than demanded by its first order condition. If firm j raises its wage infinitesimally above w^* to $w^* + \epsilon$, it will be able to fully satisfy its labor demand by the allocation mechanism. In what follows, denote $L_j^{FOC}(w_j)$ as j's labor demand under wage w_j (this is determined by j's first order condition, (5)). This upward wage deviation will be profitable if profits from $w^* + \epsilon$ are higher than profits from w^*, i.e. if the following inequality holds:

$$\theta pf\left(L_j^{FOC}(w^* + \epsilon)\right) - (w^* + \epsilon)\, L_j^{FOC}(w^* + \epsilon) > \theta pf\left(\frac{1}{J\phi}u\left(\frac{w^*}{p}\right)\right) - w^*\frac{1}{J\phi}u\left(\frac{w^*}{p}\right).$$

Note that:

$$\begin{aligned}
&\lim_{\epsilon\to 0} \quad \theta pf\left(L_j^{FOC}(w^* + \epsilon)\right) - (w^* + \epsilon)\, L_j^{FOC}(w^* + \epsilon) \\
&= \theta pf\left(L_j^{FOC}(w^*)\right) - w^* L_j^{FOC}(w^*) \\
&> \theta pf\left(\tfrac{1}{J\phi}u\left(\tfrac{w^*}{p}\right)\right) - w^*\tfrac{1}{J\phi}u\left(\tfrac{w^*}{p}\right).
\end{aligned}$$

The equality on the second line follows from the continuity of the first order condition and continuity of $f(\bullet)$. The inequality on the third line is due to the fact that at w^*, $L_j^{FOC}(w^*)$ maximizes profits. This implies that there exists some $\bar{\epsilon} > 0$ such that for all $\epsilon < \bar{\epsilon}$, profits from deviating to $w^* + \epsilon$ will be higher than maintaining wages at w^*.

Next, I show that no firm will deviate from the w^* pinned down by conditions (5) and (6).

(i) Suppose firm j raises its wage to some $w_j = w^* + \epsilon$. It follows from the first order condition, (5), that the firm will demand labor $L_j^{FOC} < L^*$. However, it could have hired L_j^{FOC} workers under wage w^*, with a lower wage bill and higher profits. This deviation cannot be profitable.

(ii) Suppose firm j lowers its wage to some $w_j = w^* - \epsilon$. The supply of workers available to j equals the mass of workers that would be willing to work for j minus the mass of workers employed by the other (higher-wage) firms:

$$\begin{aligned} L_j^{Avail} &= max\left\{\frac{1}{\bar{\phi}}u\left(\frac{w^*-\epsilon}{p}\right)-(J-1)L^*\ ,\ 0\right\} \\ &= max\left\{\frac{1}{\bar{\phi}}u\left(\frac{w^*-\epsilon}{p}\right)-\frac{J-1}{J\bar{\phi}}u\left(\frac{w^*}{p}\right)\ ,\ 0\right\}. \end{aligned}$$

Note that at $w^*-\epsilon$, $L_j^{Avail}<L^*<L_j^{FOC}$ by the above and the first order condition. This deviation will not be profitable iff $\pi_j\left(w^*,L^*\right)-\pi_j\left(w^*-\epsilon,L_j^{Avail}\right)\geq 0$.

(a) If $L_j^{Avail}=0$, then $\pi_j\left(w^*-\epsilon,L_j^{Avail}\right)=0$ and profits are trivially weakly higher from maintaining w^*.

(b) If $L_j^{Avail}>0$, then profits from maintaining w^* will be higher for J sufficiently large. First, rewrite

$$\begin{aligned} & \pi_j\left(w^*,L^*\right)-\pi_j\left(w^*-\epsilon,L_j^{Avail}\right) \\ = \ & p\theta\left[f\left(L^*\right)-f\left(L_j^{Avail}\right)\right]-\frac{\epsilon}{J\bar{\phi}}u\left(\frac{w^*}{p}\right) \\ = \ & F(J)-\frac{\epsilon}{J\bar{\phi}}u\left(\frac{w^*}{p}\right), \end{aligned}$$

where $F(J)$ is the difference in output from L^* and L_j^{Avail}. Note that:

$$\frac{\partial}{\partial J}F(J)=\frac{1}{J^2\bar{\phi}}u\left(\frac{w^*}{p}\right)p\theta\left[f'\left(L_j^{Avail}\right)-f'\left(L^*\right)\right]>0$$

by the concavity of $f(\bullet)$. Next, define $\widetilde{J}$as:

$$F(1)=\frac{\epsilon}{\widetilde{J}\bar{\phi}}u\left(\frac{w^*}{p}\right).$$

Cutting wages to $w^*-\epsilon$ will not be a profitable deviation for any J such that $F(J)-\frac{\epsilon}{J\bar{\phi}}u\left(\frac{w^*}{p}\right)>0$. The following shows this will hold for any $J\geq\widetilde{J}$.

For any positive number X:

$$\begin{aligned} F(\widetilde{J}+X) &> F(\widetilde{J}) && (since\ \tfrac{\partial}{\partial J}F(J)>0) \\ &> F(1) && (since\ \tfrac{\partial}{\partial J}F(J)>0) \\ &= \tfrac{\epsilon}{\widetilde{J}\overline{\phi}}u\left(\tfrac{w^*}{p}\right) && (by\ definition\ of\ \widetilde{J}) \\ &> \tfrac{\epsilon}{(\widetilde{J}+X)\overline{\phi}}u\left(\tfrac{w^*}{p}\right). \end{aligned}$$

Thus for J sufficiently large, profits from maintaining w^* will be higher than from deviating to $w^*-\epsilon$. This is consistent with the assumption stated in the model that J is arbitrarily large. ■

Proof of Proposition 2: Downward rigidity at the reference wage

I prove each of the two parts of Proposition 2 in turn.

(i) Define $\theta'_R = \frac{w_R}{pf'\left(\frac{1}{(J-1)\overline{\phi}}u\left(\frac{\lambda w_R}{p}\right)\right)}$. For $\theta \in (\theta'_R, \theta_R)$, no firm will deviate from wage offer w_R:

(a) Suppose firm j deviates by raising the wage to $w_j > w_R$. It follows from the first order condition, (7), that the firm will demand labor $L_j^{FOC} < \overline{L}$. However, it could have hired L_j^{FOC} workers under wage w_R, with a lower wage bill and higher profits. This deviation cannot be profitable.

(b) Suppose firm j deviates by lowering the wage to $w_j \in (\lambda w_R, w_R)$. By the firm's first order condition (7), j's labor demand will increase, but the supply of labor available to j will decrease to some L_j^{Avail}: $0 < L_j^{Avail} < \overline{L}(w_R,\theta,p)$. Then:

$$\begin{aligned} \pi_j\left(w_j, L_j^{Avail}\right) &= p\theta f\left(\lambda L_j^{Avail}\right) - w_j L_j^{Avail} \\ &< p\theta f\left(\lambda L_j^{Avail}\right) - w_R\left(\lambda L_j^{Avail}\right) && (since\ w_j > w_R\lambda) \\ &< p\theta f\left(\overline{L}(w_R,\theta,p)\right) - w_R\overline{L}(w_R,\theta,p) && (by\ FOC\ at\ w_R) \\ &= \pi_j\left(w_R, \overline{L}(w_R,\theta,p)\right). \end{aligned}$$

This deviation is not profitable.

(c) Suppose firm j deviates by lowering the wage to $w_j \leq \lambda w_R$. Since $\theta > \theta'_R$, the definition of θ'_R above implies:

$$\overline{L}\left(w_R, \theta, p\right) > \frac{1}{(J-1)\overline{\phi}} u\left(\frac{\lambda w_R}{p}\right).$$

As a result, the supply of labor available to j is:

$$\begin{aligned} L_j^{Avail} &= max\left\{\tfrac{1}{\overline{\phi}} u\left(\tfrac{w_j}{p}\right) - (J-1)\bar{L}\ ,\ 0\right\} \\ &\leq max\left\{\tfrac{1}{\overline{\phi}} u\left(\tfrac{\lambda w_R}{p}\right) - (J-1)\bar{L}\ ,\ 0\right\} \quad (since\ w_j \leq w_R\lambda) \\ &= 0 \quad (by\ the\ expression\ for\ \overline{L}\ above). \end{aligned}$$

The profits from cutting to $w_j \leq \lambda w_R$ are therefore 0. This deviation is not profitable.

The first order condition (7) implies that for $\theta \in (\theta'_R, \theta_R)$, $\overline{L}\left(w_R, \theta, p\right) < \overline{L}\left(w_R, \theta_R, p\right)$. This is because the wage remains fixed at w_R, while $\theta < \theta_R$, and $f(\bullet)$ is concave. Since by the definition of θ_R, $J\overline{L}\left(w_R, \theta_R, p\right) = \frac{1}{\overline{\phi}} u\left(\frac{w_R}{p}\right)$, this impies that for $\theta \in (\theta'_R, \theta_R)$, $J\overline{L}\left(w_R, \theta, p\right) < \frac{1}{\overline{\phi}} u\left(\frac{w_R}{p}\right)$. Thus, there will be excess labor supply in the market.

Finally, note that $\lim\limits_{\lambda\to 0} \theta'_R = \lim\limits_{\lambda\to 0} \frac{w_R}{pf'\left(\frac{1}{(J-1)\overline{\phi}} u\left(\frac{\lambda w_R}{p}\right)\right)} = 0.$

(ii) The definition of θ_R and Proposition 1 imply: $\overline{w}\left(w_R, \theta_R, p\right) = w^*\left(\theta_R, p\right) = w_R$. Since $\frac{\partial w^*(\theta,p)}{\partial \theta} > 0$ for all θ, $w^*\left(\theta_R, p\right) \geq w_R$ for $\theta \geq \theta_R$. The below arguments show that for $\theta \geq \theta_R$, no firm will want to deviate from $\overline{w}\left(w_R, \theta, p\right) = w^*\left(\theta, p\right)$:

(a) Suppose firm j raises its wage to some $w_j = \overline{w}\left(w_R, \theta, p\right) + \epsilon > w_R$. Since $w_j > w_R$, j's first order condition (7) coincides with the benchmark case. This deviation cannot be profitable by the same logic as part (i) of the proof of Proposition 1 above.

(b) Suppose firm j lowers its wage to some $w_j = \overline{w}\left(w_R, \theta, p\right) - \epsilon \geq w_R$. (Note that this implies $\theta > \theta_R$). The firm's choice of labor demand at w_j is given by first order condition (7). This deviation cannot be profitable by the same logic as part (ii) of the proof of Proposition 1 above.

(c) Suppose firm j lowers its wage to some $w_j = \overline{w}(w_R, \theta, p) - \epsilon < w_R$. Define $L_j^{FOC,\lambda}$ implicitly as: $p\theta\lambda f'\left(\lambda L_j^{FOC,\lambda}\right) = w_j$. In addition, define $L_j^{FOC,B}$ implicitly as: $p\theta f'\left(L_j^{FOC,B}\right) = w_j$. Note that by condition (8), $L_j^{FOC,\lambda} < L_j^{FOC,B}$. At w_j, j's optimal labor demand will correspond to $L_j^{FOC,\lambda}$. There are 2 possibilities:

1) If $L_j^{FOC,\lambda} > L_j^{Avail}$, then the amount of labor hired by the firm will correspond to L_j^{Avail} (the available labor supply). Then:

$$\begin{aligned}
\pi_j\left(w_j, L_j^{Avail}\right) &= p\theta f\left(\lambda L_j^{Avail}\right) - w_j L_j^{Avail} \\
&\leq p\theta f\left(L_j^{Avail}\right) - w_j L_j^{Avail} \qquad (since\ \lambda < 1) \\
&< p\theta f(L^*) - w^* L^* \qquad (by\ Proposition\ 1\ proof) \\
&= p\theta f\left(\overline{L}\right) - \overline{w}\overline{L} \\
&= \pi_j\left(\overline{w}, \overline{L}\right)
\end{aligned}$$

2) If $L_j^{FOC,\lambda} \leq L_j^{Avail}$, then the amount of labor hired by the firm will correspond to $L_j^{FOC,\lambda}$. Then:

$$\begin{aligned}
\pi_j\left(w_j, L_j^{FOC,\lambda}\right) &= p\theta f\left(\lambda L_j^{FOC,\lambda}\right) - w_j L_j^{FOC,\lambda} \\
&< p\theta f\left(L_j^{FOC,\lambda}\right) - w_j L_j^{FOC,\lambda} \qquad (since\ \lambda < 1) \\
&< p\theta f\left(L_j^{FOC,B}\right) - w_j L_j^{FOC,B} \qquad (by\ FOC\ condn\ (5)) \\
&< p\theta f(L^*) - w^* L^* \qquad (by\ Proposition\ 1\ proof) \\
&= p\theta f\left(\overline{L}\right) - \overline{w}\overline{L} \\
&= \pi_j\left(\overline{w}, \overline{L}\right)
\end{aligned}$$

Thus, such a downward deviation cannot be profitable.

Since $\overline{w}(w_R, \theta_R, p) = w^*(\theta_R, p)$ for $\theta \geq \theta_R$, this implies $\overline{L}(w_R, \theta_R, p) = L^*(\theta_R, p)$ because labor demand under the first order conditions (5) and (7) coincides for $w \geq w_R$. As a result, condition (6) implies $J\overline{L}(w_R, \theta, p) = \frac{1}{\phi} u\left(\frac{\overline{w}(w_R, \theta, p)}{p}\right)$ for $\theta \geq \theta_R$. ■

Proof of Proposition 3: Distortions from reference wage increases

Since, from Proposition 2, $\frac{\partial \theta'_S}{\partial \lambda} > 0$ and $\lim_{\lambda \to 0} \theta'_S = 0$, for λ sufficiently small, it follows that $\overline{w}(w_S, \theta, p) = w_s$ for $\theta \leq \theta_S$.

First note that for $\theta \in (\theta_R, \theta_S)$:

$$\begin{aligned}
\overline{w}(w_R, \theta, p) &= w^*(\theta, p) && by\, Proposition\, 2 \\
&< w^*(\theta_S, p) && by\, Corollary\, 1 \\
&= w_S && by\, definition\, of\, \theta_S
\end{aligned}.$$

In addition, for $\theta \leq \theta_R$, $\overline{w}(w_R, \theta, p) \leq w_R < w_S$, where the first inequality follows from Proposition 2. Together, the above imply that $\overline{w}(w_R, \theta, p) < w_s$ for $\theta < \theta_S$.

Since Proposition 3 assumes $\overline{w}(w_S, \theta, p) = w_S$ for $\theta < \theta_S$, this implies: $\overline{w}(w_R, \theta, p) < w_S = \overline{w}(w_S, \theta, p)$ for $\theta < \theta_S$. Then, $\overline{L}(w_S, \theta, p) < \overline{L}(w_R, \theta, p)\; for\; \theta < \theta_S$ by the firm's first order condition (7). ■

Proof of Proposition 4: Inflation will mitigate distortions from nominal rigidity

Suppose that $\overline{w}\left(w_R, \widetilde{\theta}, \widetilde{p}\right) = w_R\; and\; J\overline{L}\left(w_R, \widetilde{\theta}, \widetilde{p}\right) < \frac{1}{\phi} u\left(\frac{\overline{w}(w_R, \widetilde{\theta}, \tilde{p})}{p}\right)$. As the price level rises above $\widetilde{p}$, holding the wage fixed at w_R, the first order condition (7) implies that labor demand will rise, while (2) implies that labor supply will fall. There will be a $p' > \widetilde{p}$ at which aggregate labor demand will be exactly equal to aggregate supply. This p' is pinned down by the following condition:

$$p'\widetilde{\theta} f'\left(\frac{1}{J\bar{\phi}} u\left(\frac{w_R}{p'}\right)\right) = w_R.$$

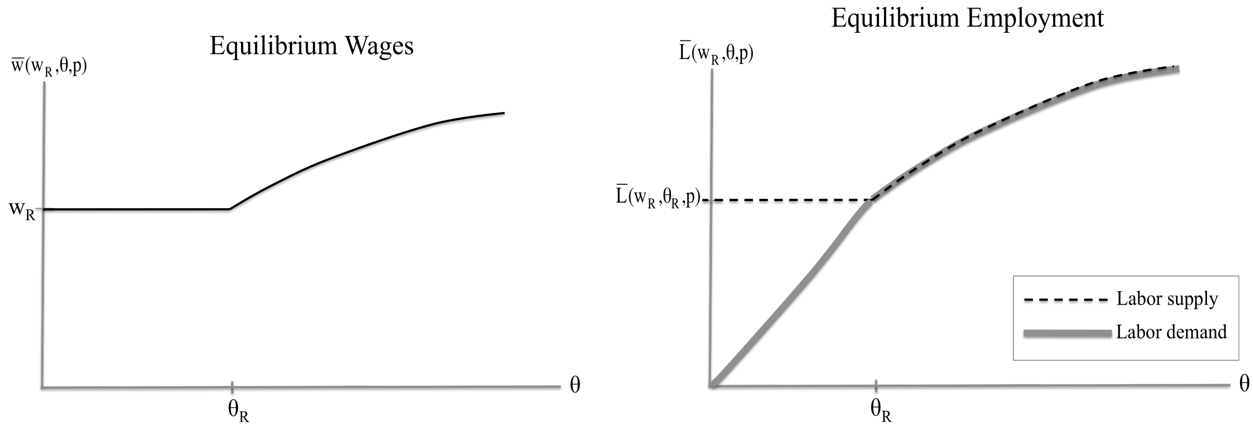
Note that at p' and $\widetilde{\theta}$, w_R is the market clearing wage. This implies that: $\overline{w}\left(w_R, \widetilde{\theta}, p'\right) = w^*\left(\widetilde{\theta}, p'\right) = w_R$. In addition, for any $p'' \geq p'$:

$$\begin{aligned}
\overline{w}\left(w_R, \widetilde{\theta}, p'\right) &= w_R && by\, definition\, of\, p'. \\
&= w^*\left(\widetilde{\theta}, p'\right) && \\
&\leq w^*\left(\widetilde{\theta}, p''\right) && since\, \tfrac{\partial w^*}{\partial p} > 0 \\
&= \overline{w}\left(w_R, \widetilde{\theta}, p''\right) && by\, Proposition\, 2\, since\, w^*\left(\widetilde{\theta}, p''\right) \geq w_R
\end{aligned}.$$

Thus, $\forall p \geq p'$, $\overline{w}\left(w_R, \widetilde{\theta}, p\right) = w^*\left(\widetilde{\theta}, p\right)$. In addition, this implies $\overline{L}\left(w_R, \widetilde{\theta}, p\right) = L^*\left(\widetilde{\theta}, p\right)$ since $\overline{w}\left(w_R, \widetilde{\theta}, p\right) \geq w_R$ and also implies market clearing by Proposition 2. ■

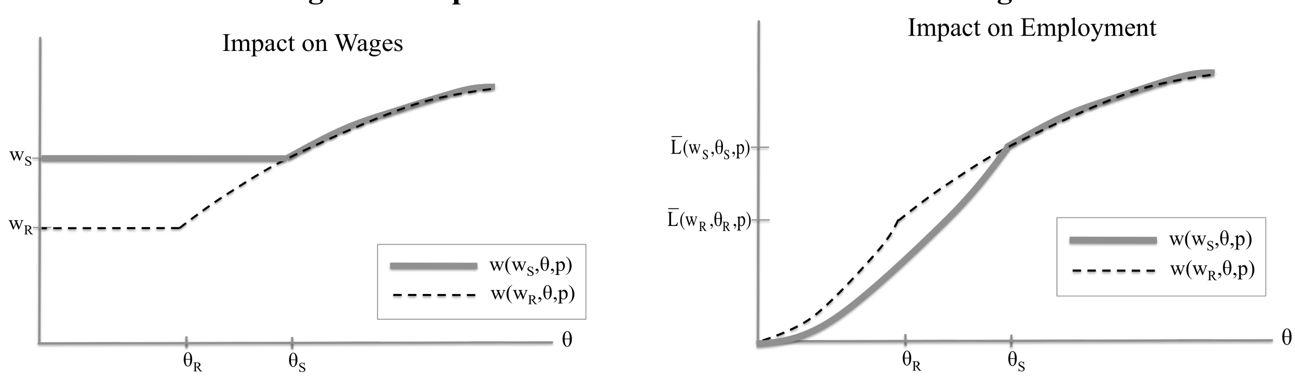
B. Figures and Tables

Figure 1: Labor Market Outcomes under Rigidity



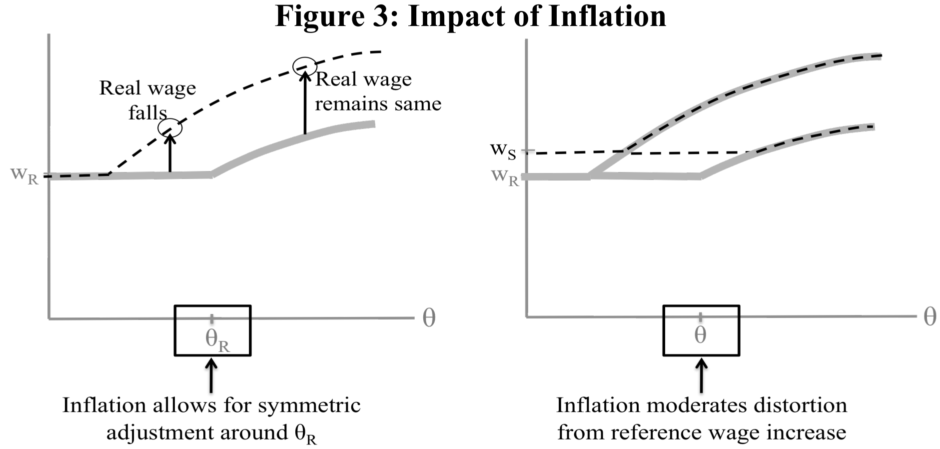
Notes: This figure illustrates the relationship between wages and θ, and employment and θ (Proposition 2 of the model). The figure is drawn for the case of $\lambda \approx 0$.

Figure 2: Impact of an Increase in the Reference Wage



Notes: This figure illustrates the impact of an increase in the reference wage on equilibrium wages and employment (Proposition 3 of the model). The figure is drawn for the case of $\lambda \approx 0$.

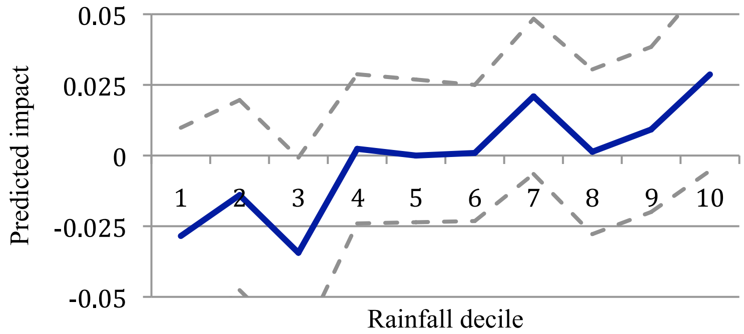
Figure 3: Impact of Inflation



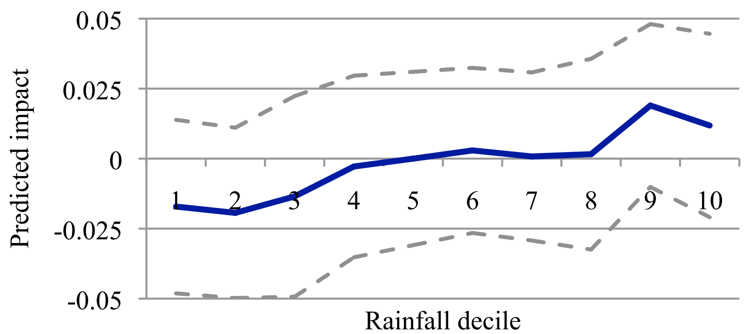
Notes: This figure illustrates the impact of inflation in moderating wage distortions (Proposition 4 of the model). The graph on the left demonstrates the impact of an increase in price levels on equilibrium wages. The graph on the right illustrates the impact of inflation under an increase in the reference wage. The figure is drawn for the case of $\lambda \approx 0$.

Figure 4
Impact of Rainfall on Agricultural Outcomes

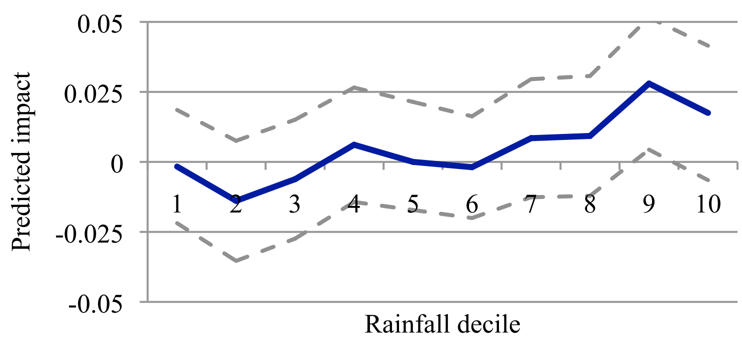
Panel A: Log Crop Yield



Panel B: Agricultural Employment Rate



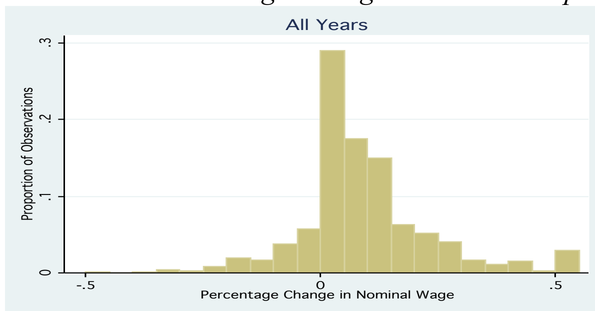
Panel C: Log Nominal Agricultural Wage



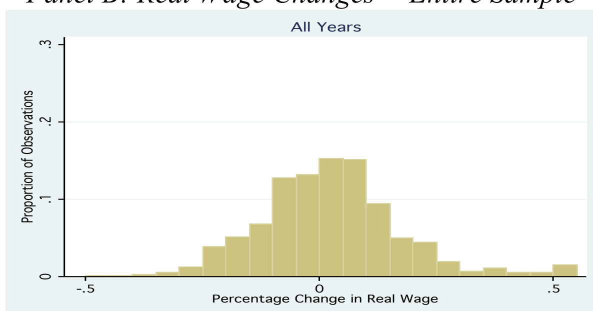
Notes:
1. This figure shows the impact of rainfall on 3 outcome measures—log agricultural yields (from the World Bank data), the employment rate for workers in the agricultural labor force (from the NSS data), and the log nominal daily agricultural wage (in the World Bank data).
2. The panels plot coefficients from a regression of each outcome on dummies for each decile of the rainfall distribution and district and year fixed effects. Each decile dummy equals 1 if the district's rainfall in the current year fell within the given decile of the district's usual rainfall distribution and equals 0 otherwise. The 5th decile is the omitted category in each regression. The coefficients on the decile dummies are shown, along with 95% confidence intervals. The confidence interval for the 5th decile is computed by averaging the confidence intervals for the 4th and 6th deciles.
3. Standard errors are corrected to allow for clustering by region-year.

Figure 5
Distributions of Wage Changes

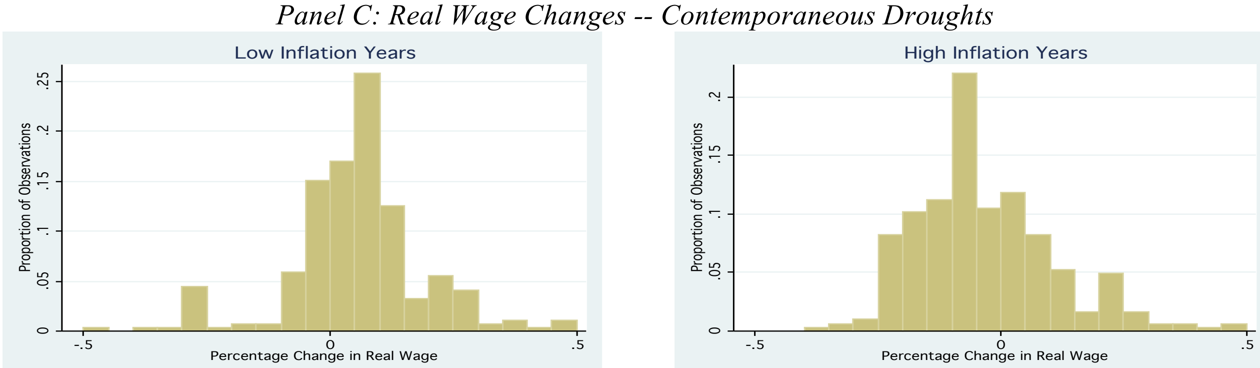
Panel A: Nominal Wage Changes -- Entire Sample



Panel B: Real Wage Changes -- Entire Sample



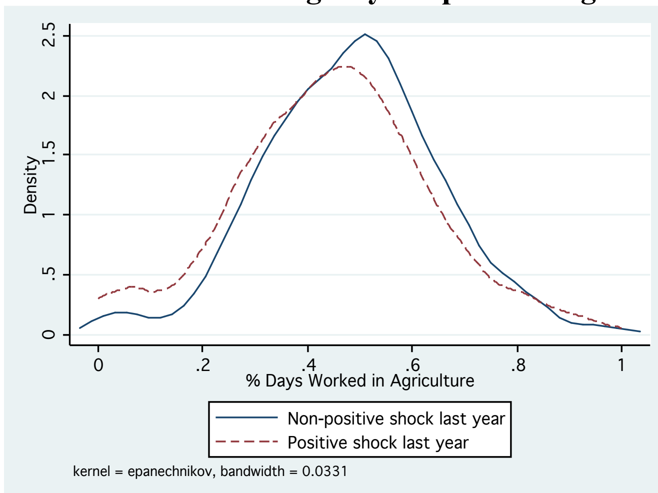
Panel C: Real Wage Changes -- Contemporaneous Droughts



Panel D: Real Wage Changes -- Lag Positive Shocks

Notes:
1. This figure shows distributions of year-to-year percentage changes in agricultural wages in the World Bank dataset.
2. The unit of observation is a district-year. Real wages are computed as the nominal wage divided by the state CPI for agricultural workers. Low (high) inflation years are defined as years in which the state inflation rate was below (above) the sample median of 6%. Droughts and positive shocks are defined as rainfall in the first month of the monsoon below the 20th percentile and above the 80th percentile, respectively, of the district's usual rainfall distribution in that month.
3. Panel A shows nominal wage changes in the entire sample (8,401 district-years). The observations in Panels B-D are drawn from the 4,642 district-years for which state CPI data is available. Panel B shows real wage changes in this sample. Panel C uses observations in which a district experienced a drought in that year. Panel D uses observations in which a district experienced a positive shock in the previous agricultural year. Panels C and D show distributions separately for low and high inflation years.

Figure 6
Employment Distortions from Rigidity: Impact of Lag Positive Shocks



Notes:
1. This figure displays the impact of lag positive shocks on the distribution of agricultural employment in the NSS data.
2. The outcome variable is the mean of the percentage of days in the interview reference period in which agricultural workers were employed in agricultural work (own farm work plus hired out work) in each district-year.
3. A positive (non-positive) shock in a district-year is defined as rainfall above (below) the 80th percentile of the district's rainfall distribution.
4. The solid line plots kernel density estimates of the outcome variable for district-years in which there was a non-positive shock in the previous year and a non-positive shock in the current year. The dashed line plots kernel density estimates for district-years in which there was a positive shock in the previous year and a non-positive shock in the current year.
5. The estimates use the Epanechnikov kernel function. The bandwidth minimizes the mean integrated squared error assuming a Gaussian distribution and kernel.

Table 1
Summary Statistics

Variable	Mean	Standard Deviation	Observations: District-years	Observations: Individual-years	Source
Rainfall shocks					
% Positive Shocks (1956-1987)	0.222	0.416	7,296	--	Univ of Delaware
% Droughts (1956-1987)	0.150	0.357	7,296	--	Univ of Delaware
% Positive Shocks (1982-2008)	0.178	0.383	3,419	--	Univ of Delaware
% Droughts (1982-2008)	0.186	0.389	3,419	--	Univ of Delaware
Wage and employment variables					
Log nominal agricultural wage (1956-1987)	1.200	0.815	7,296	--	World Bank
Log nominal agricultural wage (1982-2008)	3.279	0.890	--	154,578	Natl Sample Survey
Agricultural employment rate	0.494	0.484	--	1,003,431	Natl Sample Survey
Other measures					
Log crop yields index	0.237	0.271	7,296	--	World Bank
Acres per adult in household	0.776	8.260	--	1,003,431	Natl Sample Survey
Inflation rate	0.074	0.079	6,384	--	Agricultrl Prices in India, Consumer Price Indices

Notes:
1. This table presents summary statistics for variables used in the analysis. Means and standard deviations are presented for each variable.
2. % Positive shocks and % Droughts gives the percentage of district-years in the data in which there was a positive rainfall shock or drought, respectively. A positive shock is defined as rainfall in the first month of the monsoon above the 80th percentile of the district's usual distribution and a drought is defined as rainfall below the 20th percentile of the district's usual distribution.
3. Log nominal agricultural wage is the log of the mean nominal daily wage for a male ploughman in the World Bank data during a district-year, and the log of the nominal daily wage for agricultural activities for an individual in the National Sample Survey data.
4. Log crop yields index is defined as the log of a composite index measure of the yields variable. The index is a weighted mean of yields of all 20 crops for which yields data are available, where the yield has first been normalized by the mean yield of that crop in the district. Weights are the mean percentage of landarea planted with a given crop in a district.
5. The national inflation rate is defined as the mean change in the CPI in the past agricultural year. For the years 1956-1962, this is computed from the national Working Class Living Index. For the years 1965-1987, this is computed by taking the average of the state CPI for Agricultural Workers across all states in the World Bank sample.

Table 2
Effect of Shocks on Equilibrium Wages
Dependent Variable: Log Nominal Daily Agricultural Wage

			Source: World Bank Data (1956-1987)			Source: NSS Data (1982-2008)		
			(1)	(2)	(3)	(4)	(5)	(6)
	$Shock_{t-1}$	*$Shock_t$*						
1	Zero	Zero	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted
2	Drought	Zero	0.003	Omitted	Omitted	0.002	Omitted	Omitted
			(0.011)			(0.015)		
3	Zero	Positive	0.021			0.045		
			(0.010)**			(0.012)***		
4	Drought	Positive	0.064	0.026	0.026	0.079	0.052	0.052
			(0.019)***	(0.009)***	(0.009)***	(0.028)***	(0.011)***	(0.011)***
5	Positive	Positive	0.014			0.066		
			(0.016)			(0.023)***		
6	Zero	Drought	-0.006			0.006		
			(0.013)	-0.010	-0.010	(0.016)	-0.003	-0.002
				(0.011)	(0.011)		(0.013)	(0.013)
7	Drought	Drought	-0.015			-0.025		
			(0.018)			(0.028)		
8	Positive	Drought	0.038	0.037		0.115	0.114	
			(0.021)*	(0.020)*	0.024	(0.018)***	(0.019)***	0.056
					(0.010)**			(0.013)***
9	Positive	Zero	0.021	0.021		0.026	0.025	
			(0.010)**	(0.010)**		(0.014)*	(0.015)*	
District and year FE?			Yes	Yes	Yes	Yes	Yes	Yes
Additional controls?			No	No	No	Yes	Yes	Yes
Obs: district-years			7,296	7,296	7,296	--	--	--
Obs: individual-years			--	--	--	154,476	154,476	154,476
Dependent var mean			1.197	1.197	1.197	3.261	3.261	3.261

Notes:
1.This table tests for the impacts of sequences of shocks on the agricultural wage.
2. The dependent variable is the log of the nominal daily agricultural wage.
3. The shocks are defined as drought, zero, or positive, and correspond to rainfall below the 20th percentile, between the 20th-80th percentiles, and above the 80th percentile, respectively. The covariates are indicators that equal 1 if a given sequence of shocks was realized and zero otherwise. The sequences are presented as the shock in the previous year and the shock in the current year.
4. Columns (1) and (3) omit the sequence {Zero, Zero} and include separate dummies for each of the remaining 8 combinations of shocks. The remaining columns group shocks into categories with similar predictions. Columns (2) and (4) also omit the sequence {Drought, Zero}; combine rows 3-5 into one indicator function for whether the district experienced a contemporaneous positive shock; and combine rows 6-7 into an indicator function for whether the district had a zero shock or drought last year followed by a contemporaneous drought. Columns (3) and (6) repeat this specification, but also combine rows 8-9 into one indicator for whether the district had a positive shock last year followed by a drought or zero shock this year.
5. Each regression also contains year and district fixed effects. Regressions (4)-(6) from the NSS data also include fixed effects for calendar quarters of the year and a dummy for gender.
6. Standard errors are corrected to allow for clustering by region-year.

Table 3: Impact of Inflation on Wage Distortions

Dependent Variable: Log Nominal Daily Agricultural Wage

		Definition of Lag Positive Shocks: Positive shock in previous year			*Definition of Lag Positive Shocks:* At least one positive shock in last 3 years		
			Continuous measure: Inflation rate	*Binary measure:* Inflation > 6%		*Continuous measure:* Inflation rate	*Binary measure:* Inflation > 6%
		(1)	(2)	(3)	(4)	(5)	(6)
	{$Shock_{t-1}$=Drought or Zero}; {$Shock_t$=Zero}	Omitted	Omitted	Omitted	Omitted	Omitted	Omitted
1	{$Shock_{t-1}$=Drought, Zero, or Positive}; {$Shock_t$=Positive}	0.017	0.020	0.021	0.024	0.035	0.034
		(0.009)*	(0.011)*	(0.011)*	(0.010)**	(0.011)***	(0.012)***
2	{$Shock_{t-1}$=Drought, Zero, or Positive}; {$Shock_t$=Positive} x Inflation measure		-0.031	-0.006		-0.127	-0.017
			(0.101)	(0.017)		(0.109)	(0.018)
3	{$Shock_{t-1}$=Drought or Zero}; {$Shock_t$=Drought}	-0.020	0.000	0.001	-0.038	0.014	-0.004
		(0.011)*	(0.014)	(0.016)	(0.015)***	(0.018)	(0.020)
4	{$Shock_{t-1}$=Drought or Zero}; {$Shock_t$=Drought} x Inflation measure		-0.254	-0.036		-0.577	-0.056
			(0.156)	(0.023)		(0.188)***	(0.028)**
5	{$Shock_{t-1}$=Positive}; {$Shock_t$=Drought}	0.019	0.039	0.061	0.028	0.040	0.057
		(0.020)	(0.034)	(0.033)*	(0.016)*	(0.024)*	(0.027)**
6	{$Shock_{t-1}$=Positive}; {$Shock_t$=Drought} x Inflation measure		-0.218	-0.080		-0.154	-0.057
			(0.251)	(0.040)**		(0.198)	(0.034)*
7	{$Shock_{t-1}$=Positive}; {$Shock_t$=Zero}	0.015	0.044	0.042	0.029	0.049	0.052
		(0.011)	(0.016)***	(0.018)**	(0.008)***	(0.012)***	(0.014)***
8	{$Shock_{t-1}$=Positive}; {$Shock_t$=Zero} x Inflation measure		-0.336	-0.047		-0.248	-0.040
			(0.128)***	(0.021)**		(0.096)***	(0.017)**
	Year and district fixed effects?	Yes	Yes	Yes	Yes	Yes	Yes
	F-test p-value: Coefficient 3 + Coefficient 4 = 0	--	--	0.027**	--	--	0.002***
	F-test p-value: Coefficient 5 + Coefficient 6 = 0	--	--	0.400	--	--	0.990
	F-test p-value: Coefficient 7 + Coefficient 8 = 0	--	--	0.678	--	--	0.207

Notes:

1. This table tests whether inflation mitigates distortions from rigidity. Observations are from the 6,384 district-years in the World Bank data for which inflation data is available (the years 1956-87 except 1960, 1963-64, and 1975). The dependent variable is the log of the nominal daily agricultural wage; the dependent variable mean is 1.27.
2. Shocks are defined as drought, zero, or positive, and correspond to rainfall below the 20th percentile, between the 20th-80th percentiles, and above the 80th percentile, respectively. Covariates 1,3,5, and 7 are of the form {$Shock_{t-1}$=X};{$Shock_t$=Y}; they are indicators that equal 1 if the district experienced shock X in the previous year and shock Y in the current year, and equal 0 otherwise. The other covariates are interactions of these sequences of shocks with measures of inflation.
3. In Columns (1)-(3), {$Shock_{t-1}$=Positive} refers to having a positive shock in the previous year; in columns (4)-(6), this refers to having at least one positive shock in the last 3 years. In all columns, {$Shock_{t-1}$=Drought or Zero} refers to having a drought or zero shock in the previous year.
4. Columns (1) and (4) show OLS regressions of the dependent variable on the sequences of shocks. Columns (2) and (5) add interactions of each shock category with the national inflation rate. Columns (3) and (6) add interactions of each shock category with an indicator for whether the national inflation rate was above 6%.
5. Each regression contains year and district fixed effects. Standard errors are corrected to allow for clustering by region-year.

Table 4: Effect of Shocks on Employment

Dependent variable: Total worker-days in agriculture

Sample		Full Sample (1)	Full Sample (2)	Lean Season Excluded (3)
	Panel A: Average Impact of Lag Positive Shocks			
	Lag positive shock	-0.111	-0.217	-0.220
		(0.046)**	(0.049)***	(0.052)***
	Lag positive shock x Acres per adult in household		0.141	0.139
			(0.029)***	(0.028)***
	Panel B: Full Specification			
	{$Shock_{t-1}$=Drought or Zero; $Shock_t$=Zero}	Omitted	Omitted	Omitted
1	{$Shock_{t-1}$=Drought, Zero, or Positive}; {$Shock_t$=Positive}	0.078	0.078	0.104
		(0.047)*	(0.047)*	(0.051)**
2	{$Shock_{t-1}$=Drought, Zero, or Positive}; {$Shock_t$=Positive} x Acres per adult in household		-0.006	-0.005
			(0.005)	(0.004)
3	{$Shock_{t-1}$=Drought or Zero}; {$Shock_t$=Negative}	0.116	-0.112	-0.095
		(0.049**	(0.050)**	(0.051)*
4	{$Shock_{t-1}$=Drought or Zero}; {$Shock_t$=Drought} x Acres per adult in household		-0.001	-0.001
			(0.015)	(0.013)
5	{$Shock_{t-1}$=Positive}; {$Shock_t$=Drought}	-0.244	-0.352	-0.365
		(0.076)***	(0.073)***	(0.074)***
6	{$Shock_{t-1}$=Positive}; {$Shock_t$=Drought} x Acres per adult in household		0.123	0.135
			(0.037)***	(0.038)***
7	{$Shock_{t-1}$=Positive}; {$Shock_t$=Zero}	-0.107	-0.213	-0.205
		(0.058)*	(0.064)***	(0.072)***
8	{$Shock_{t-1}$=Positive}; {$Shock_t$=Zero} x Acres per adult in household		0.151	0.132
			(0.040)***	(0.038)***
9	Acres per adult in household	0.047	0.007	0.037
		(0.015)***	(0.002)***	(0.014)***
10	(Acres per adult in household)^2	-1.04×10^{-5}	-1.50×10^{-6}	-7.73×10^{-6}
		(3.37×10^{-6})***	(5.40x10-7)***	(3.02×10^{-6})**
F-test p-value: Coefficient 3 = Coefficient 5		0.117	0.002***	0.001***
Observations: individual-years		1,003,030	1,003,030	755,347
Dependent variable mean		3.48	3.48	3.62

Notes:

1. This table tests for employment impacts of shocks. The dependent variable is the number of worker-days in the last 7 days in which the worker was employed in agricultural work (own farm work plus hired out work). Columns (1)-(2) include all observations for agricultural workers (workers whose primary or subsidiary work activity is agriculture). Column (3) excludes observations for the lean quarter (April-June).
2. Shocks are defined as drought, zero, or positive, and correspond to rainfall below the 20th percentile, between the 20th-80th percentiles, and above the 80th percentile, respectively.
3. Panel A shows regressions of the dependent variable on an indicator for whether the district experienced a positive shock in the previous year, and an interaction of this indicator with acres per adult in the household.
4. In Panel B, covariates 1,3,5, and 7 are of the form {$Shock_{t-1}$=X};{$Shock_t$=Y}; they are indicators that equal 1 if the district experienced shock X in the previous year and shock Y in the current year, and equal 0 otherwise. The other covariates are interactions of these sequences of shocks with acres per adult in the household.
5. Each regression also contains year fixed effects, district fixed effects, fixed effects for calendar quarters of the year, a gender dummy, and a quadratic function of acres per adult in the household.
6. Standard errors are corrected to allow for clustering by region-year.

Table 5: Separation - Compositional Effects on Employment

	Dependent Variable	*Household's worker-days as agric laborer* (1)	*Household's worker-days on own farm* (2)	*Household's total worker-days in agric* (3)
	Panel A: Average Impact of Lag Positive Shocks			
	Lag positive shock	-0.797	0.502	-0.230
		(0.283)***	(0.228)**	(0.269)
	Lag positive shock x Medium landholding	0.641	-0.523	0.118
		(0.270)**	(0.240)**	(0.269)
	Lag positive shock x Large landholding	0.870	-1.216	-0.346
		(0.321)***	(0.288)***	(0.314)
	Panel B: Full Specification			
	{Shock$_{t-1}$=Drought or Zero; Shock$_t$=Zero}	Omitted	Omitted	Omitted
1	{Shock$_{t-1}$=Drought, Zero, or Positive}; {Shock$_t$=Positive}	0.446	0.599	1.045
		(0.303)	(0.299)**	(0.289)***
2	{Shock$_{t-1}$=Drought, Zero, or Positive}; {Shock$_t$=Positive} x Medium landholding	-0.392	-0.170	-0.562
		(0.315)	(0.336)	(0.283)**
3	{Shock$_{t-1}$=Drought, Zero, or Positive}; {Shock$_t$=Positive} x Large landholding	-0.580	-0.238	-0.818
		(0.339)*	(0.392)	(0.369)**
4	{Shock$_{t-1}$=Drought or Zero}; {Shock$_t$=Drought}	-1.506	-0.014	-1.521
		(0.427)***	(0.269)	(0.401)***
5	{Shock$_{t-1}$=Drought or Zero}; {Shock$_t$=Drought} x Medium landholding	1.192	-0.126	1.066
		(0.439)***	(0.324)	(0.420)**
6	{Shock$_{t-1}$=Drought or Zero}; {Shock$_t$=Drought} x Large landholding	1.556	0.118	1.673
		(0.448)***	(0.367)	(0.430)***
7	{Shock$_{t-1}$=Positive}; {Shock$_t$=Drought}	-0.913	0.322	-0.592
		(0.392)**	(0.326)	(0.401)
8	{Shock$_{t-1}$=Positive}; {Shock$_t$=Drought} x Medium landholding	0.812	-0.274	0.538
		(0.439)*	(0.381)	(0.392)
9	{Shock$_{t-1}$=Positive}; {Shock$_t$=Drought} x Large landholding	0.938	-1.047	-0.109
		(0.472)**	(0.439)**	(0.495)
10	{Shock$_{t-1}$=Positive}; {Shock$_t$=Zero}	-1.234	0.701	-0.533
		(0.444)***	(0.313)**	(0.426)
11	{Shock$_{t-1}$=Positive}; {Shock$_t$=Zero} x Medium landholding	0.896	-0.676	0.220
		(0.379)**	(0.333)**	(0.401)
12	{Shock$_{t-1}$=Positive}; {Shock$_t$=Zero} x Large landholding	1.328	-1.402	-0.073
		(0.499)***	(0.388)***	(0.491)
Observations: household-years		203,073	203,073	203,073
Dependent variable mean		3.31	7.06	10.38

Notes:
1. This table tests if the composition of household labor supply is consistent with separation failures. The dependent variables are the total number of worker-days in the last 7 days spent by all members of the household employed as an agricultural laborer (col 1), on own farm work (col 2), and total agricultural labor supply (own farm work plus hired out work) (col 3). The sample comprises agricultural households with positive land and excludes observations for the lean quarter (April-June).
2. Shocks are defined as drought, zero, or positive, and correspond to rainfall below the 20th percentile, between the 20th-80th percentiles, and above the 80th percentile, respectively. Medium and large landholding are indicators for whether acres per adult in the household is in the second or third tercile of the sample distribution, respectively.
3. Panel A shows regressions of the dependent variable on an indicator for whether the district experienced a positive shock in the previous year, and an interaction of this indicator with landholding terciles.
4. In Panel B, covariates 1,3,5, and 7 are of the form {Shock$_{t-1}$=X};{Shock$_t$=Y}; they are indicators that equal 1 if the district experienced shock X in the previous year and shock Y in the current year, and equal 0 otherwise. The other covariates are interactions of these sequences of shocks with landholding terciles.
5. Each regression contains year, district, and calendar quarter fixed effects, quadratic functions of the number of males and females in the household. Standard errors are corrected to allow for clustering by region-year.

Table 6
Heterogeneity in Wage Rigidity: Sensitivity of Crops to Labor Inputs
Dependent Variable: Log Nominal Wage

		District Crop Sensitivity Measure			
		% Land with Sensitive Crops: *Average over Last 5 Years*		% Land with Sensitive Crops: *Average over Entire Sample*	
		Continuous measure: % landarea	Binary measure: % landarea is above median	Continuous measure: % landarea	Binary measure: % landarea is above median
		(1)	(2)	(3)	(4)
	{$Shock_{t-1}$=Drought or Zero}; {$Shock_t$=Zero}	Omitted	Omitted	Omitted	Omitted
1	{$Shock_{t-1}$=Drought, Zero, or Positive}; {$Shock_t$=Positive}	0.027	0.020	0.025	0.028
		(0.009)***	(0.010)**	(0.009)***	(0.009)***
2	{$Shock_{t-1}$=Drought, Zero, or Positive}; {$Shock_t$=Positive} x District crop sensitivity measure	-0.061	0.014	-0.130	-0.005
		(0.137)	(0.015)	(0.146)	(0.014)
3	{$Shock_{t-1}$=Drought or Zero}; {$Shock_t$=Drought}	-0.009	0.016	-0.010	0.010
		(0.011)	(0.015)	(0.011)	(0.013)
4	{$Shock_{t-1}$=Drought or Zero}; {$Shock_t$=Drought} x District crop sensitivity measure	-0.425	-0.045	-0.263	-0.039
		(0.200)**	(0.020)**	(0.184)	(0.018)**
5	{$Shock_{t-1}$=Positive}; {$Shock_t$=Drought}	0.044	0.069	0.036	0.033
		(0.021)**	(0.032)**	(0.020)*	(0.021)
6	{$Shock_{t-1}$=Positive}; {$Shock_t$=Drought} x District crop sensitivity measure	-0.351	-0.042	-0.148	0.008
		(0.325)	(0.036)	(0.293)	(0.033)
7	{$Shock_{t-1}$=Positive}; {$Shock_t$=Zero}	0.022	0.017	0.020	0.028
		(0.010)**	(0.011)	(0.010)*	(0.010)***
8	{$Shock_{t-1}$=Positive}; {$Shock_t$=Zero} x District crop sensitivity measure	-0.142	0.010	-0.206	-0.015
		(0.160)	(0.018)	(0.166)	(0.017)
9	District crop sensitivity measure	-0.375	-0.028	--	--
		(0.205)*	(0.012)**		
District and year fixed effects?		Yes	Yes	Yes	Yes
Observations: district-years		6,840	6,840	7,296	7,296
F-test p-value: Coefficient 3 + Coefficient 4 + Coefficient 9 = 0		--	0.001***	--	0.061*
F-test p-value: Coefficient 5 + Coefficient 6 + Coefficient 9 = 0		--	0.970	--	0.175
F-test p-value: Coefficient 7 + Coefficient 8 + Coefficient 9 = 0		--	0.962	--	0.398

Notes:
1. This table tests whether district with crops that are more sensitive to labor inputs have less rigid wages. Observations are from the World Bank dataset. The dependent variable is the log of the district's mean nominal daily wage.
2. Shocks are defined as drought, zero, or positive, and correspond to rainfall below the 20th percentile, between the 20th-80th percentiles, and above the 80th percentile, respectively. Covariates 1, 3, 5, and 7 are of the form {$Shock_{t-1}$=X};{$Shock_t$=Y}; they are indicators that equal 1 if the district experienced shock X in the previous year and shock Y in the current year, and equal 0 otherwise. The other covariates are interactions of these sequences of shocks with district crop sensitivity measures.
3. Crop sensitivity measures capture the percentage of landarea in the district planted with crops that are highly sensitive to the amount of labor hired (soybeans, sesame, rapseed/mustard, sunflowers, and sugarcane). The crop sensitivty measures were constructed as follows. For each of the 5 crops, the percentage of landarea planted with the crop in each district-year was regressed on year fixed effects to remove national time trends. The residuals for each of the 5 regressions were then summed to give the total adjusted percentage of land planted with these crops in each district-year. Columns (1)-(2) use the mean of the total adjusted percentage in each district over the last 5 years. Columns (3)-(4) use the district's mean of the total adjusted percentage in the sample as a whole. In both cases, the percentage values from the current year and previous year are excluded when computing means. In columns (1) and (3), the district crop sensitivity measure is the continuous mean percentage. In columns (2) and (4), the district crop sensitivity measure is a binary indicator that equals 1 if the mean percentage is above the sample median and zero otherwise.
4. Each regression also contains district and year fixed effects. Standard errors are corrected to allow for clustering by region-year.
5. The last 3 rows report p-values of F-tests for sums of coefficients as indicated. For the regressions in columns (3)-(4), coefficient 9 is absorbed by the district fixed effects; this coefficient is therefore not included in the sums in column (4).

Table 7
Fairness Norms in Rural Labor Markets

		Proportion Selecting Unfair			
			State Breakup		
		Full Sample	Orissa	Madhya Pradesh	Differ-ence
	Panel A: Acceptability of Wage Reductions				
1	A farmer hires a laborer to weed his land for 1 day at a wage of Rs. 120. There is a local factory that pays Rs. 100 per day. One month later, the factory shuts down and many people in the area become unemployed.				
	A) … After this, the farmer decides to do a second weeding and hires the same laborer as before at a wage of Rs. 100.	0.62	0.74	0.49	0.24***
	B) … After this, the farmer decides to do a second weeding and hires one of the newly unemployed laborers at a wage of Rs. 100.	0.55	0.72	0.36	0.36***
2	A farmer usually pays laborers Rs. 120 per day. His son becomes sick and the medical bills are very expensive. He lowers the wage to Rs. 110 per day.	0.79	0.79	0.79	0.00
	Panel B: Money Illusion				
3	Last year, the prevailing wage in a village was Rs. 100 per day. This year, the rains were very bad and so crop yields will be lower than usual.				
	A) … There has been no change in the cost of food and clothing. Farmers decrease this year's wage rate from Rs. 100 to Rs. 95 per day.	0.64	0.81	0.45	0.36***
	B) …. The price of food and clothing has increased so that what used to cost Rs. 100 before now costs Rs. 105. Farmers keep this year's wage rate at Rs. 100.	0.38	0.42	0.32	0.10
	C) … The price of food and clothing has increased since last year, so that what used to cost Rs. 100 before now costs Rs. 110. Farmers increase this year's wage rate from Rs. 100 to Rs. 105.	0.09	0.08	0.09	0.00
4	A farmer usually pays laborers Rs. 100 per day plus food. There is not much work in the area and many laborers are looking for work. He stops providing food but continues to pay Rs. 100.	0.29	0.24	0.34	-0.11*
	Panel C: Market Clearing Mechanisms				
5	A farmer needs to hire a laborer to plough his land. There is not much work in the area at that time, and 5 laborers want the job. The farmer asks each of them to state the lowest wage at which they are willing to work, and then hires the laborer who stated the lowest wage.	0.61	0.75	0.45	0.29***
6	A farmer needs to hire a laborer to plough his land. The prevailing rate in the area is Rs. 120 per day. The farmer knows there is a laborer who needs money to meet a family expense and is having difficulty finding work. The farmer offers the job to that laborer at Rs. 110 per day.	0.53	0.65	0.38	0.27***
7	It is harvest time and all farmers in a village pay laborers Rs. 120 per day. One large farmer decides to harvest some of his land immediately and needs to hire 10 laborers. To find enough laborers, he pays them Rs. 150 per day for one week. In the following weeks, he decides to harvest the rest of his land, and re-hires 5 of the laborers at Rs. 120 per day.	0.63	0.81	0.43	0.38***
8	There are 20 landowners in a village. The prevailing wage during plowing time is Rs. 120. 10 landowners want to attract extra laborers, and they increase the wage they pay to Rs. 130. The other 10 landowners don't need much labor and maintain the wage at Rs. 120.	0.45	0.60	0.27	0.33***

Panel D: Fairness Norms and Effort

9 A farmer needs a laborer to weed his land. The prevailing wage is Rs. 120. There isn't much work in the area and many want the job. A laborer named Balu has family expenses for which he desperately needs money. The farmer knows of Balu's situation, and so he offers him the job at: A) Rs. 120 B) Rs. 100. Given his need for money, Balu accepts the job. How carefully will he do the weeding?

	More carefully than usual	With the normal amount of care	Less carefully than usual
A) Rs. 120	0.55	0.44	0.01
B) Rs. 100	0.06	0.54	0.40

Notes:
1. This table presents survey evidence on fairness norms in rural labor markets. Respondents were presented with the scenarios in the table and asked to rate each scenario as "Very fair", "Fair", "Unfair", or "Very Unfair". The table shows the percentage of respondents that selected "Unfair" or "Very Unfair" in response to each scenario. Each respondent only received half the scenarios presented in the table. In the case of paired scenarios (questions 1A/1B, 3A/3C, and 9A/9B), each respondent was asked only 1 of the scenarios in each pair.
2. The sample is comprised of 396 respondents (196 casual agricultural laborers and 200 landowning farmers) from 34 villages in the Indian states of Orissa and Madhya Pradesh. All respondents were males aged 20-80. Interviews were conducted July-August 2011.

Table 8
Survey Responses to Employment Scenarios

			Proportion of Responses		
				State Breakup	
			Full Sample	Orissa	Madhya Pradesh
	Panel A: Laborers (N=196)				
1	If a laborer was willing to accept work at a rate lower than the prevailing wage, would he be more likely to obtain work from farmers in the village?	Yes	0.61	0.53	0.70
		Maybe	0.20	0.19	0.22
		No	0.19	0.28	0.09
2	When you have difficulty finding work at the prevailing wage, do you offer to work at a lower wage?	Yes	0.31	0.08	0.58
		Sometimes	0.22	0.16	0.28
		No	0.47	0.76	0.14
3	Suppose the prevailing wage is Rs. 100 per day. You have been unemployed for a long time and are in urgent need of money. If a farmer offers you Rs. 95 for one day of work, would you accept the job?	Yes	0.58	0.38	0.79
		Maybe	0.24	0.38	0.09
		No	0.18	0.23	0.12
	Panel B: Landowners (N=200)				
4	In non-peak periods, have you ever hired a laborer for agricultural work at a wage below the prevailing wage?	Yes	0.05	0.03	0.09
		No	0.95	0.97	0.91
5	Suppose the prevailing non-peak wage rate is Rs. 100. There is a laborer in your village who has been unemployed for a long time and is in urgent need of money. If a farmer offers him Rs. 95 for one day of work, would the laborer accept the job?	Yes	0.39	0.14	0.67
		Maybe	0.25	0.38	0.09
		No	0.37	0.48	0.24
6	Suppose you need to hire a laborer to work during the non-peak period. The prevailing wage is Rs. 100. There is a laborer who would accept the job at Rs. 95 because of money problems. What wage rate would you offer him?	Rs. 95	0.40	0.27	0.54
		Rs. 100	0.60	0.73	0.46

Notes:
1. This table tabulates responses of agricultural workers and employers to survey questions.
2. The sample is comprised of 396 respondents (196 casual agricultural laborers and 200 landowning farmers) from 34 villages in the Indian states of Orissa and Madhya Pradesh. All respondents were males aged 20-80. Interviews were conducted July-August 2011.

Appendix Tables

Appendix Table 1
Test for Serial Correlation in Rainfall

Dependent variable: District's rainfall deviation in the current year

	Sample			
	World Bank data districts (1956 - 1987)		NSS data districts (1982 - 2008)	
	(1)	(2)	(3)	(4)
District's rainfall deviation in the previous year	-0.048 (0.035)	-0.056 (0.033)*	-0.018 (0.033)	-0.016 (0.030)
District and year fixed effects?	No	Yes	No	Yes
Observations: district-years	8,672	8,672	15,392	15,392

Notes:
1. This table tests for serial correlation in rainfall. The unit of observation in each regression is a district-year. Regressions (1)-(2) perform the analysis for the districts in the World Bank dataset for rainfall over the years 1956-1987. Regressions (3)-(4) perform the analysis for the districts in the NSS dataset for rainfall over the years 1986-2007.
2. The dependent variable is a district's rainfall deviation, which equals the rainfall level in inches in the first month of the monsoon minus the district's mean rainfall level in that month in the sample.
3. Each column shows results of an OLS regression of the dependent variable on the district's rainfall deviation in the previous year. The regressions in columns (2) and (4) also include year fixed effects and district fixed effects.
4. Standard errors in each regression are corrected to allow for clustering by geographic region, as defined in the NSS data.

Appendix Table 2
Rainfall Shocks: Test for Differential Impacts by Season

	Dependent Variable	
	Log nominal wage	% Days Worked in Agriculture
	(1)	(2)
Positive shock	0.046	0.026
	(0.014)***	(0.012)**
Positive shock x	-0.015	-0.013
Harvest quarter (October-December)	(0.017)	(0.012)
Positive shock x	-0.023	-0.008
Post-harvest quarter (January-March)	(0.022)	(0.015)
Positive shock x	0.021	-0.027
Lean quarter (April-June)	(0.017)	(0.019)
Drought	0.023	-0.023
	(0.018)	(0.011)**
Drought x	0.023	-0.004
Harvest quarter (October-December)	(0.022)	(0.011)
Drought x	-0.018	0.015
Post-harvest quarter (January-March)	(0.022)	(0.014)
Drought x	-0.003	0.003
Lean quarter (April-June)	(0.023)	(0.018)
Harvest quarter (October-December)	0.035	0.010
	(0.010)***	(0.006)
Post-harvest quarter (January-March)	0.060	-0.054
	(0.011)***	(0.008)***
Lean quarter (April-June)	0.086	-0.097
	(0.011)***	(0.011)***
F-test p-value: Joint significance of interaction terms	0.118	0.546
Year and district fixed effects?	Yes	Yes
Obs: individual-years	154,476	1,002,005
Dependent var mean	3.244	0.483

Notes:
1.This table tests whether rainfall shocks have differential effects by season over the agricultural year.
2. Observations are from the NSS data. The dependent variable in Column (1) is the log of the nominal daily agricultural wage. The dependent variable in Column (2) is the percentage of days over the interview reference period that the worker was employed in agricultural activities.
3. Positive shock is an indicator that equals 1 if the district experienced rainfall in the first month of the monsoon above the 80th percentile and equals 0 otherwise. Drought is an indicator that equals 1 if the district experienced rainfall below the 20th percentile and equals 0 otherwise.
4. Each column shows results from an OLS regression of the dependent variable on rainfall shocks, dummies for quarter of the year, and interactions of each shock with quarters. The monsoon quarter (July-September) is omitted. Each regression contains year and district fixed effects and a dummy for gender. Regression (2) also contains a quadratic function of acres per adult in the household.
5. Standard errors are corrected to allow for clustering by region-year.

Appendix Table 3
Specification Check: Effect of Shocks on Equilibrium Wages

Dependent Variable: Log Nominal Agricultural Wage

		Source: World Bank Data (1956-1987)			Source: NSS Data (1982-2008)		
		(1)	(2)	(3)	(4)	(5)	(6)
1	Positive shock	0.021	0.022	0.021	0.041	0.042	0.041
		(0.009)**	(0.009)**	(0.010)**	(0.010)***	(0.010)***	(0.012)***
2	Drought	-0.003	-0.003	-0.006	0.026	0.018	0.004
		(0.011)	(0.011)	(0.012)	(0.012)**	(0.011)	(0.016)
3	Lag positive shock		0.019	0.021		0.044	0.021
			(0.009)**	(0.010)**		(0.011)***	(0.014)
4	Lag drought		0.009	0.003		-0.002	-0.000
			(0.009)	(0.011)		(0.013)	(0.015)
5	Positive shock x Lag positive shock			-0.028			0.006
				(0.018)			(0.030)
6	Drought x Lag drought			-0.011			-0.029
				(0.022)			(0.034)
7	Positive shock x Lag drought			0.039			0.017
				(0.020)*			(0.031)
8	Drought x Lag positive shock			0.023			0.086
				(0.021)			(0.026)***
	F-test p-value: joint signif of Coeff 3, 5, & 8			0.042**			0.000***
	F-test p-value: joint significance of Coeff 3-8			0.020**			0.000**
	District and year FE?	Yes	Yes	Yes	Yes	Yes	Yes
	Additional controls?	No	No	No	Yes	Yes	Yes
	Obs: district-years	7,296	7,296	7,296	--	--	--
	Obs: individual-years	--	--	--	154,476	154,476	154,476
	Dependent var mean	1.197	1.197	1.197	3.261	3.261	3.261

Notes:
1.This table tests for the impacts of sequences of shocks on the agricultural wage.
2. The dependent variable is the log of the nominal daily agricultural wage.
3. Positive shock is an indicator that equals 1 if the district experienced rainfall above the 80th percentile in the current year and equals 0 otherwise. Drought is an indicator that equals 1 if the district experienced rainfall below the 20th percentile in the current year and equals 0 otherwise. Lag positive shock (Lag drought) is an indicator that equals 1 if the district experienced a positive shock (drought) in the previous year and equals 0 otherwise.
4. Each regression contains year and district fixed effects. Regressions (4)-(6) from the NSS data also include fixed effects for calendar quarters of the year and a dummy for gender.
5. Standard errors are corrected to allow for clustering by region-year.

Appendix Table 4
Persistence of Lagged Shocks
Dependent Variable: Log Nominal Daily Agricultural Wage

	Source: World Bank Data (1956-1987)			*Source: NSS Data (1982-2008)*		
	(1)	(2)	(3)	(4)	(5)	(6)
Positive shock this year	0.021	0.022	0.022	0.041	0.042	0.041
	(0.009)**	(0.009)**	(0.009)***	(0.010)***	(0.010)***	(0.009)***
Positive shock 1 year ago		0.019	0.020		0.044	0.042
		(0.009)**	(0.009)**		(0.011)***	(0.011)***
Positive shock 2 years ago			0.030			0.007
			(0.009)***			(0.013)
Positive shock 3 years ago			0.028			-0.012
			(0.010)***			(0.011)
Drought this year	-0.003	-0.003	-0.005	0.026	0.018	0.019
	(0.011)	(0.011)	(0.010)	(0.012)**	(0.011)	(0.011)*
Drought 1 year ago		0.009	0.009		-0.002	-0.001
		(0.009)	(0.009)		(0.013)	(0.013)
Drought 2 years ago			0.006			-0.009
			(0.009)			(0.013)
Drought 3 year ago			0.008			0.004
			(0.009)			(0.014)
District and year FE?	Yes	Yes	Yes	Yes	Yes	Yes
Obs: district-years	7,296	7,296	7,296	--	--	--
Obs: individual-years	--	--	--	154,476	154,476	154,476
Dependent var mean	1.197	1.197	1.197	3.261	3.261	3.261

Notes:
1.This table tests for the persistence of lag shocks on the agricultural wage.
2. The dependent variable is the log of the nominal daily agricultural wage. Columns (1)-(4) use observations from the World Bank data. Columns (5)-(7) use observations from the NSS data.
3. Positive shock is an indicator that equals 1 if the district experienced rainfall above the 80th percentile and equals 0 otherwise. Drought is an indicator that equals 1 if the district experienced rainfall below the 20th percentile and equals 0 otherwise. Each covariate is an indicator for whether the district experienced a positive shock or drought in the current or in a previous year, as described in the table.
4. Each regression contains year and district fixed effects. Regressions (4)-(6) from the NSS data also include fixed effects for calendar quarters of the year and a dummy for gender.
5. Standard errors are corrected to allow for clustering by region-year.

Appendix Table 5
Inflation Results: Robustness Checks

		Dependent variable = Inflation rate		Dependent variable = Log nominal wage		
				Interaction Term in Regressions		
				Inflation in other states	*Linear year trend*	*Post-1970 year dummy*
		(1)	(2)	(3)	(4)	(5)
	$\{Shock_{t-1}$=Drought or Zero$\}$; $\{Shock_t$=Zero$\}$	Omitted	Omitted	Omitted	Omitted	Omitted
1	$\{Shock_{t-1}$=Drought, Zero, or Positive$\}$; $\{Shock_t$=Positive$\}$	-0.023	-0.023	0.014	0.017	0.023
		(0.011)*	(0.012)*	(0.009)	(0.010)*	(0.016)
2	$\{Shock_{t-1}$=Drought, Zero, or Positive$\}$; $\{Shock_t$=Positive$\}$ x Interaction term			-0.024	-0.000	-0.010
				(0.123)	(0.001)	(0.022)
3	$\{Shock_{t-1}$=Drought or Zero$\}$; $\{Shock_t$=Drought$\}$	0.006	0.007	0.004	-0.020	-0.021
		(0.018)	(0.019)	(0.012)	(0.013)	(0.018)
4	$\{Shock_{t-1}$=Drought or Zero$\}$; $\{Shock_t$=Drought$\}$ x Interaction term			-0.280	0.000	0.002
				(0.160)*	(0.001)	(0.026)
5	$\{Shock_{t-1}$=Positive$\}$; $\{Shock_t$=Drought$\}$	0.003	0.004	0.025	0.019	0.001
		(0.014)	(0.015)	(0.025)	(0.023)	(0.029)
6	$\{Shock_{t-1}$=Positive$\}$; $\{Shock_t$=Drought$\}$ x Interaction term			-0.240	-0.000	0.028
				(0.216)	(0.002)	(0.039)
7	$\{Shock_{t-1}$=Positive$\}$; $\{Shock_t$=Zero$\}$	0.005	0.005	0.032	0.014	0.009
		(0.010)	(0.010)	(0.017)*	(0.011)	(0.016)
8	$\{Shock_{t-1}$=Positive$\}$; $\{Shock_t$=Zero$\}$ x Interaction term			-0.247	0.001	0.010
				(0.120)*	(0.001)	(0.024)
District fixed effects?		No	Yes	Yes	Yes	Yes
Year fixed effects?		No	No	Yes	Yes	Yes
Observations: district-years		6,384	6,384	5,016	6,384	6,384
Dependent variable mean		1.27	1.27	1.58	1.27	1.27

Notes:
1. This table provides robustness checks for the inflation results.
2. Observations are from the World Bank data. The sample in all columns except column (3) is comprised of the years for which national inflation data is available (the years 1956-87 except 1960, 1963-64, and 1975). The sample in column (3) is comprised of the years for which state inflation data is available (the years 1965-87, except 1975).
3. Shocks are defined as drought, zero, or positive, and correspond to rainfall below the 20th percentile, between the 20th-80th percentiles, and above the 80th percentile, respectively. Covariates 1, 3, 5, and 7 are of the form $\{Shock_{t-1}=X\};\{Shock_t=Y\}$; they are indicators that equal 1 if the district experienced shock X in the previous year and shock Y in the current year, and equal 0 otherwise. The other covariates are interactions of these sequences of shocks with various controls.
4. Columns (1)-(2) show results of OLS regressions of the national inflation rate on the sequences of shocks. Regression (2) also includes district fixed effects.
5. Columns (3)-(5) show results of OLS regressions of the log nominal daily agricultural wage on the sequences of shocks and interactions. The interaction term in regression (3) equals the average inflation rate across all states except the district's own state. The interaction term in regression (5) is a linear trend--the de-meaned calendar year. The interaction term in column (6) is an indicator that equals one if the year is after 1970 and equals 0 otherwise. Each of these regressions contains year and district fixed effects.
6. Standard errors in all regressions are corrected to allow for clustering by year.

Appendix Table 6
Effect of Shocks on Employment
Dependent Variable: Agricultural Employment Rate

	$Shock_{t-1}$	$Shock_t$	(1)	(2)
1	Zero	Zero	Omitted	Omitted
2	Drought	Zero	0.011 (0.008)	Omitted
3	Zero	Positive	0.016 (0.009)*	
4	Drought	Positive	-0.008 (0.016)	0.011 (0.007)*
5	Positive	Positive	0.030 (0.014)**	
6	Zero	Drought	-0.016 (0.009)*	-0.017 (0.007)**
7	Drought	Drought	-0.006 (0.014)	
8	Positive	Drought	-0.031 (0.011)***	-0.034 (0.011)***
9	Positive	Zero	-0.012 (0.008)	-0.015 (0.008)*
District and year FE?			Yes	Yes
Additional controls?			Yes	Yes
Obs: individual-years			1,002,005	1,002,005
Dependent var mean			0.483	0.483

Notes:
1. This table tests for the impacts of sequences of shocks on the employment rate. Observations are from the NSS data.
2. The dependent variable is the percentage of days in the interview reference period in which the worker was employed in agricultural work (own farm work plus hired out work).
3. Shocks are defined as drought, zero, or positive, and correspond to rainfall below the 20th percentile, between the 20th-80th percentiles, and above the 80th percentile, respectively. The covariates are indicators that equal 1 if a given sequence of shocks was realized and zero otherwise. The sequences are presented as the shock in the previous year and the shock in the current year.
4. Column (1) omits the sequence {Zero, Zero} and includes separate dummies for each of the remaining 8 combinations of shocks. The remaining columns group shocks into categories with similar predictions. Column (2) also omits the sequence {Drought, Zero}; combines rows 3-5 into one indicator function for whether the district experienced a contemporaneous positive shock; and combines rows 6-7 into an indicator function for whether the district had a zero shock or drought last year followed by a contemporaneous drought.
5. Each regression also contains year fixed effects, district fixed effects, fixed effects for calendar quarters of the year, a gender dummy, and a quadratic function of acres per adult in the household.
6. Standard errors are corrected to allow for clustering by region-year.

Appendix Table 7
Tests for Compositional Effects of Rainfall on Agricultural Labor Force

	Dependent Variable: Individual Migrated into Village			Dependent Variable: Individual Reports Being in Agricultural Labor Force	
	All village residents	Residents with positive agricultural employment	Members of agricultural labor force	All village residents	Residents with positive agricultural employment
	(1)	(2)	(3)	(4)	(5)
Panel A: Lag Shock Dummies					
$Shock_{t-1}$=Drought	-0.0063	-0.0069	-0.0091	0.000089	0.000408
	(0.0030)**	(0.0035)*	(0.0030)***	(0.003023)	(0.000360)
$Shock_{t-1}$=Positive	0.0042	0.0016	0.0036	-0.002853	0.000013
	(0.0039)	(0.0042)	(0.0044)	(0.002913)	(0.000326)
Panel B: Main Specification					
{$Shock_{t-1}$=Drought or Zero}; {$Shock_t$=Zero}	Omitted	Omitted	Omitted	Omitted	Omitted
{$Shock_{t-1}$=Drought, Zero, or Positive}; {$Shock_t$=Positive}	-0.0086	-0.0122	-0.0124	-0.002173	0.000064
	(0.0045)*	(0.0058)*	(0.0058)*	(0.004099)	(0.000376)
{$Shock_{t-1}$=Drought or Zero}; {$Shock_t$=Drought}	0.0007	-0.0110	-0.0010	0.000860	0.000007
	(0.0041)	(0.003)***	(0.0035)***	(0.003687)	(0.000386)
{$Shock_{t-1}$=Positive}; {$Shock_t$=Drought}	-0.0013	-0.0087	-0.0090	0.002217	-0.001012
	(0.0077)	(0.0062)	(0.0070)	(0.004710)	(0.000711)
{$Shock_{t-1}$=Positive}; {$Shock_t$=Zero}	0.0059	-0.0016	0.0018	-0.006377	0.000480
	(0.0036)*	(0.0039)	(0.0040)	(0.003218)**	(0.000366)
Observations: individual-years	973,572	278,640	381,055	2,366,290	687,913
Dependent variable mean	0.114	0.120	0.135	0.405	0.994

Notes:
1. This table tests whether rainfall shocks lead to compositional changes in the agricultural labor force. Observations are from the NSS data.
2. The dependent variable in regresionns (1)-(3) is an indicator that equals 1 if the individual is a migrant into the village and 0 otherwise. The dependent variable in regressions (4)-(5) is an indicator that equals 1 if the respondent indicated agriculture as his/her primary or subsidiary occupation, and equals 0 otherwise.
3. Panel A shows results from Probit regressions of the dependent variable on an indicator for whether the district had a positive shock in the previous year. Panel B shows results from Probit regressions of the dependent variable on categories of sequences of shocks. Estimated discrete changes are reported for each covariate.
4. Each regression also contains year fixed effects, district fixed effects, and a gender control.
5. Columns (1)-(3) use data from NSS rounds in which migration questions were asked (agricultural years 1982, 1983, 1987, and 1999). Columns (4)-(5) use data from all rounds. Estimates are reported for different subgroups of the sample as indicated. All village residents includes all respondents interviewed in the rural sample. Residents with positive agricultural employment are those respondents who report being employed in agricultural work for at least half a day in the past week. Members of the agricultural labor force are respondents who indicate that agricultural work is their primary or subsidiary occupation.
6. Standard errors are corrected to allow for clustering by region-year.