NBER WORKING PAPER SERIES

NOMINAL WAGE RIGIDITY IN VILLAGE LABOR MARKETS

Supreet Kaur

Working Paper 20770
http://www.nber.org/papers/w20770

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
December 2014, Revised November 2017

I am deeply grateful to Lawrence Katz, Michael Kremer, Sendhil Mullainathan, and Rohini Pande for feedback and encouragement. For helpful discussions, I thank Melissa Adelman, George Akerlof, Emily Breza, Lorenzo Casaburi, Katie Coffman, Tom Cunningham, Francois Gerard, Edward Glaeser, Clement Imbert, Seema Jayachandran, Asim Khwaja, David Laibson, W. Bentley MacLeod, Lauren Merrill, Emi Nakamura, Miikka Rokkanen, Frank Schilbach, Heather Schofield, Jon Steinsson, Dmitry Taubinsky, Laura Trucco, Eric Verhoogen, and numerous seminar and conference participants. I thank Prasanta Nayak for outstanding field assistance and Lakshmi Iyer for sharing the World Bank data. This project received financial support from the Project on Justice, Welfare, and Economics at Harvard University and the Giorgio Ruffolo Doctoral Fellowship in Sustainability Science at Harvard University. All errors are my own. The views expressed herein are those of the author and do not necessarily reflect the views of the National Bureau of Economic Research.

Nominal Wage Rigidity in Village Labor Markets
Supreet Kaur
NBER Working Paper No. 20770
December 2014, Revised November 2017
JEL No. E24,J31,O10,O12

ABSTRACT

This paper tests for downward nominal wage rigidity by examining transitory shifts in labor demand, generated by rainfall shocks, in 600 Indian districts from 1956-2009. Nominal wages rise in response to positive shocks but do not fall during droughts. In addition, transitory positive shocks generate ratcheting: after they have dissipated, nominal wages do not adjust back down. This ratcheting effect generates a 9% reduction in employment levels. Inflation enables downward real wage adjustments both during droughts and after positive shocks. Survey evidence suggests that workers and employers believe that nominal wage cuts are unfair and lead to effort reductions.

Supreet Kaur
Department of Economics
University of California, Berkeley
Evans Hall
Berkeley, CA 94720
and NBER
supreet@berkeley.edu

1 Introduction

This paper empirically examines downward nominal wage rigidity and its employment consequences in a developing country context. As is the case with any price, the wage allocates labor—by far the biggest factor input, especially in developing countries—to production. Adjustments in the wage are therefore what facilitate the labor market response to shocks. Rigidities may prevent wages from adjusting fully to shocks, with potentially important consequences for employment, earnings, and output. A large literature in economics has discussed these implications.[1] For example, if wages do not fall during negative shocks, this may increase layoffs—deepening the impact of recessions and exacerbating business cycle volatility. In addition, the labor rationing generated by rigidities could give rise to "disguised unemployment" or "forced entrepreneurship", creating a misallocation of labor across firms (Singh et al. 1986).

Some early work in development argued for the presence of nominal rigidities. For example, Dreze and Mukherjee (1989) observe that in casual daily labor markets in Indian villages, "The same standard wage often applies for *prolonged* periods — from several months to several years... The standard wage (in money terms)...appears to be, more often than not, rigid downwards during the slack season." Historical time series data from the Indian village of Tinur, for example, appears consistent with such observations (Figure 1). The prevailing wage follows a step-ladder progression: adjusting upwards every few years and with no apparent downward nominal adjustments over a 12-year period, including in drought years. Looking across a set of 256 districts in India, the distribution of nominal wage changes exhibits a bunching of mass at zero, with a discontinuous drop to the left of zero (Figure 2).[2] These patterns, however, could arise from measurement error such as rounding bias in reported wages. In addition, to the extent that such evidence supports wage rigidity, it does not provide insight on

[1] For overviews, see, e.g., Tobin (1972), Greenwald and Stiglitz (1987), Blanchard (1990), Clarida et al. (1999), Akerlof (2002), and Galì (2009).

[2] Under a continuous distribution of shocks, one may not expect a large discrete and asymmetric jump at nominal zero changes (McLaughlin 1994, Kahn 1997). In contrast, the distribution of real wage changes in Figure 2 appears continuous and symmetric around zero.

whether rigidities have any real consequences for employment.

These challenges apply more broadly to documenting wage rigidity in any context. The approach in existing work—almost all of which uses data from OECD countries—is based on examining distributions of wage changes, as in Figure 2. This has provided compelling documentation in OECD countries (e.g., Akerlof et al. 1996, Kahn 1997, Card and Hyslop 1997, Dickens et al. 2007, Barattieri et al. 2014, Ehrlich and Montes 2014).[3] However, this approach has made it difficult to directly examine the potential employment effects of rigidities.[4] There is little direct evidence that wage rigidity actually affects employment in the labor market in any setting.[5]

In this paper, I develop a different approach to test for wage rigidity: I isolate shocks to the marginal revenue product of labor, and examine wage adjustment and employment effects in response to these shocks.[6] I apply this approach in the context of markets for casual daily agricultural labor—a major source of employment in poor countries. In this setting, local rainfall variation generates transitory labor demand shocks. I investigate responses to these shocks in over 600 Indian districts from 1956 to 2009. My identification strategy relies on the assumption that rainfall shocks are transitory: monsoon rainfall affects total factor productivity (TFP) in the current year, but does not directly affect TFP in future years. I validate this assumption below.

Wage adjustment is consistent with downward rigidities. First, adjustment is asym-

[3] However, more recently, studies have failed to find downward rigidity using this approach. This has led to mixed evidence for downward rigidity in the aftermath of the Great Recession (Fallick et al. 2015, Elsby et al. 2016, Verdugo 2016).

[4] This approach typically limits analysis to workers employed by the same firm in consecutive years. This also creates challenges for inference: if workers quit when they anticipate wage cuts, then wage cuts will appear less frequent than they actually are. On the other hand, measurement error can make wage cuts appear more frequent than they actually are.

[5] A notable exception is Card (1990), who examines union workers whose nominal wages are explicitly indexed to expected inflation. As a result, real wages cannot adjust to inflation surprises, leading firms to adjust employment. Card and Hyslop (1997) examine whether periods of higher inflation are correlated with smaller impacts of negative shocks on unemployment in labor markets in the US, and do not find evidence for a relationship. There remains a debate as to whether wage rigidity has any relevance for employment dynamics (e.g., Pissarides 2009, Elsby 2009, Rogerson and Shimer 2011, Schmitte-Grohe and Uribe 2013).

[6] Holzer and Montgomery (1993) perform analysis in this spirit. They assume sales growth reflects demand shifts, and examine correlations of wage and employment growth with sales growth in the U.S. They find that wages changes are asymmetric and are small compared to employment changes.

metric. Relative to no shock, nominal wages rise in response to positive shocks, but are no lower during negative shocks on average. Second, transitory positive shocks generate ratcheting. When a positive shock in one year is followed by a non-positive shock in the following year, nominal wages do not adjust back down—they are higher than they would have been in the absence of the lagged transitory positive shock.

Third, particularly consistent with *nominal* rigidity, inflation moderates these wage distortions.[7] When inflation is higher, negative shocks are more likely to result in lower real wages, and previous transitory positive shocks are less likely to have persistent wage effects. When inflation is above 6%, I cannot reject that lagged positive shocks have no impact on current real wages. In contrast, inflation has no differential effect on upward real wage adjustment to current positive shocks—consistent with downward nominal rigidities. These findings support the hypothesis that inflation "greases the wheels" of the labor market.

When rigidities bind—keeping real wages above market clearing levels—this distorts employment. If a district experiences a transitory positive shock (and therefore has a ratcheted wage in the following year), total agricultural employment is 9% lower in the following year than if the lagged positive shock had not occurred.[8] In contrast, these shocks have no effect on non-agricultural hiring. 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.

The brunt of the employment decreases after lagged positive shocks is borne by poorer individuals—the landless and small landholders—who are the primary suppliers of hired agricultural labor. When they are rationed out of the external labor market, small landholders increase labor supply to their own farms. These findings are consistent with the prediction that labor rationing will lead to "disguised unem-

[7]In the presence of nominal rigidities, inflation will enable real wages to adjust downward without requiring any nominal wage cuts. Because local rainfall shocks do not affect—and are therefore uncorrelated with—inflation, this enables a causal test of whether inflation affects real wage adjustment.

[8]Total agricultural employment is total worker-days spent in farm work—whether on one's own land or as hired labor on someone else's land. This effect is driven by a decreased in hired employment.

ployment" and separation failures, with smaller farms using labor more intensively in production than larger farms (Singh, Squire, and Strauss 1986; Benjamin 1992).[9]

Could the above findings be explained by factors other than nominal wage rigidity? There are two categories of potential concerns. The first is a violation of the assumption that shocks are transitory. The second is that rainfall affects labor supply or demand through other channels, such as migration or capital accumulation. While such explanations could account for a portion of my findings, I argue that the full pattern of results—wages, employment, and inflation—is most consistent with downward nominal wage rigidity. In addition, in supplementary analyses, I fail to find evidence in support of such alternate explanations.

The results point to the relevance of nominal rigidities in a setting with few of the institutional constraints that have received prominence in the empirical literature on wage rigidity. In villages, minimum wage legislation is largely ignored and formal unions are rare (Rosenzweig 1980, 1988). Wage contracts are typically bilaterally arranged between employers and workers and are of short duration (usually one day), making it potentially easier for contracts to reflect changes in market conditions (Dreze and Mukherjee 1989).

A growing body of evidence argues that nominal wage cuts are perceived as unfair, causing decreases in worker productivity.[10] Following Kahneman, Knetsch, and Thaler (1986), I presented 396 agricultural laborers and employers in 34 villages across 6 districts 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 nominal wage cuts violate fairness norms. For example, the majority of respondents thought it was

[9] In the presence of rationing, a household's labor supply decision will not be separable from its decision of how much labor to use on its farm. This is a prominent hypothesis for why smaller farms tend to use more labor per acre and have higher yields per acre than larger farms—a widely documented phenomenon in poor countries (e.g. Bardhan 1973, Udry 1996). These results lend some support to this hypothesis. Behrman (1999) reviews the empirical literature on separation failures.

[10] 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). See Fehr, Goette, and Zehnder (2009) for a broader discussion of the relevance of fairness preferences in labor markets.

unfair to cut nominal wages after a surge in unemployment (62%) or during a severe drought (64%). In contrast, relatively few people thought that a real wage cut is unfair if it is achieved through inflation (9%). Respondents also expressed a strong belief that workers decrease effort when fairness norms are violated.[11]

This paper is closely linked to the literature on labor market distortions in poor countries. Early theoretical work in development focused heavily on labor market imperfections.[12] However, there has been no direct empirical documentation of downward wage rigidity in this setting to date. There is a broader empirical literature on the functioning of labor markets in developing countries. Some studies find results consistent with competitive markets exhibiting real wage and employment adjustments to shocks (Rosenzweig 1980, Benjamin 1992, Jayachandran 2006, Mobarak and Rosenzweig 2014, Imbert and Papp 2015, Muralidharan et al. 2016). Other studies find evidence consistent with imperfections such as separation failures (Bardhan 1973, Udry 1996, Foster et al. 1997, Barrett et al. 2008, Foster and Rosenzweig 2011, LaFave and Thomas 2016).[13] These two strands of evidence should not be viewed as contradictory. The findings in this paper indicate that in this setting, real wages do adjust often in response to market forces and play an allocative role. However, in cases when nominal rigidities bind, thereby distorting real wages, this affects employment—with the potential to contribute to labor market imperfections.

The rest of the paper proceeds as follows. Section 2 presents a model of nominal wage rigidity. Section 3 lays out the empirical strategy and Section 4 presents the results. Section 5 evaluates whether explanations other than nominal rigidity are consistent the results. Section 6 discusses mechanisms and presents survey evidence for the role of fairness norms in villages. Section 7 concludes. The Online Appendix

[11] Of course, survey responses may not reflect actions under real stakes. To the extent that these responses reflect fairness norms, they do not provide insight on the micro-foundations for these norms.

[12] For example, Lewis (1954), Eckaus (1955), Rosenstein-Rodan (1956), Leibenstein (1957), Kao et al. (1964), Shapiro and Stiglitz (1984), Singh et al. (1986). Many of the early theories for labor rationing have not withstood empirical scrutiny. Rosenzweig (1988) provides an excellent review of the evidence for some of these theories, such as nutrition efficiency wages.

[13] Other recent papers explore other related topics, such as labor supply elasticity (Goldberg 2016), credit and labor allocation (Fink, Jack, and Masiye 2014), and migration (Morten 2016; Bryan, Chowdhury, and Mobarak 2014; McKenzie, Theoharides, and Yang 2014).

contains all appendix materials, including appendix figures and tables.

2 Model

I model a small open economy with decentralized wage setting and exogenous product prices. Rigidities arise because workers view nominal wage cuts as unfair, and retaliate to such cuts by decreasing effort.[14] I use this framework to develop testable implications of fairness preferences on labor market outcomes. For simplicity, what follows is a static model of the labor market, in which employers and workers make decisions about the current period, taking the previous period's wages as given. At the end of the section, I discuss implications of a multi-period dynamic setting.

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 $\phi_i \sim U\left[0, \overline{\phi}\right]$, which equals worker i's cost of supplying 1 unit of effective labor. 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: $u\left(\frac{w}{p}\right) - \phi_i e R\left(\lambda, w, \bar{w}_{t-1}\right)$, where p is the price level and $R\left(\cdot\right)$ captures reference dependence in utility around the previous period's average market wage, $\bar{w}_{t-1}$.[15] Specifically, I assume $R\left(\lambda, w, \bar{w}_{t-1}\right) = 1 + \frac{1-\lambda}{\lambda} 1\left\{w < \bar{w}_{t-1}\right\}$. This means that when $w < \bar{w}_{t-1}$, the disutility of work, $\phi_i e$, is scaled up by $\frac{1-\lambda}{\lambda}$, where $\lambda \in (0, 1]$. The case of $\lambda = 1$ corresponds to the benchmark of no reference dependence. Note that time subscripts are omitted from w, p, and e for simplicity of notation, since all results in the model will pertain to period t (the current period), taking as given $\bar{w}_{t-1}$.

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

[14] In Section 6, I provide support for this modeling assumption using survey evidence.

[15] In Indian villages, at any point in time, there is a gender-specific prevailing wage; any agricultural worker employed in the village is typically paid this wage. Thus, the average market wage in the previous period would also correspond to the individual's own wage in the previous period.

firm, she reduces effort to exactly offset the disutility from the fairness violation:

$$e = \begin{cases} 1 & w \geq \bar{w}_{t-1} \\ \lambda & w < \bar{w}_{t-1} \end{cases}. \tag{1}$$

Consequently, worker i's payoff from accepting wage offer w always reduces to $u\left(\frac{w}{p}\right) - \phi_i$. In the model, I take this fairness norm as exogenous.[16] More generally, it can be conceptualized as the reduced form for a strategy in a repeated game. I normalize the payoff from not working as 0. When all firms offer w, aggregate labor supply is: $L^S = \frac{1}{\phi}u\left(\frac{w}{p}\right)$.

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:

$$\pi_j = p\theta f\left(eL_j\right) - w_j L_j, \tag{2}$$

where $f(\cdot)$ is a continuous, increasing, twice-differentiable concave function, and output depends on effective labor, eL_j. I assume θ is a non-negative stochastic productivity parameter whose realization is common to all firms. In the empirical strategy, θ corresponds to the current year's rainfall realization.

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. For simplicity, I assume each firm hires the available workers with the lowest ϕ-values that are willing to work for it.[17]

[16] Other fairness norm-based efficiency wage models of wage rigidity—e.g. Akerlof and Yellen (1990), Eliaz and Spiegler (2013), and Benjamin (2015)—also assume exogenous rules for effort decreases.

[17] Specifying an allocation mechanism by which workers are matched to firms is needed to formalize the impact of off-equilibrium deviations on firm profits in the model proofs. The mechanism described here ensures that the firms offering the highest wage receive priority in hiring. In addition, it 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.

2.2 Benchmark Case: No Rigidity

In the benchmark case (i.e. when $\lambda = 1$), $e = 1$ for all wage levels. Firm j's profits are therefore: $\pi_j = p\theta f(L_j) - w_j L_j$. I focus on the symmetric pure strategy Nash Equilibrium, in which all firms offer the same wage:[18] $w_j = w^*(\theta, p)\, \forall j$, where $w^*(\theta, p)$ will be used to denote the equilibrium wage level in the benchmark case. The firm's first order condition pins down the optimal choice of labor:

$$p\theta f'(L^*) = w^*. \tag{3}$$

The market clearing condition is:

$$JL^* = \frac{1}{\phi} u\left(\frac{w^*}{p}\right). \tag{4}$$

Lemma 1: Market clearing in benchmark case.

If workers do not exhibit fairness preferences, the unique pure strategy symmetric Nash Equilibrium will satisfy conditions (3) and (4). The labor market will clear for all realizations of θ.

Proof: See Appendix B.1. ■

Note that (3) and (4) correspond exactly to the conditions in a competitive equilibrium.

Corollary: Null Hypotheses.

(1) *The equilibrium wage will be monotonically increasing in θ: If $\theta' < \theta''$, then $w^*(\theta', p) < w^*(\theta'', p)$.*

(2) *The equilibrium wage, $w^*(\theta, p)$, is not affected by the previous period's wage, $\bar{w}_{t-1}$.*

(3) *The price level has no impact on the real wage. Consequently, for any $\theta' < \theta''$, $\left(\frac{w^*(\theta'', p)}{p} - \frac{w^*(\theta', p)}{p}\right)$ is not affected by changes in p.*

Null hypotheses (1) and (2) follow directly from Lemma 1. For (3), it is straightforward to verify from (3) and (4): $\frac{\partial w^*(\theta,p)}{\partial p} = \frac{w^*}{p}$ and $\frac{\partial L^*(\theta,p)}{\partial p} = 0$. If there is a price

[18] Since all employers in a village typically pay the same prevailing wage, in this setting it is reasonable to focus on pure strategy symmetric equilibria.

increase, firms raise nominal wages to keep real wages constant and employment therefore does not change. Consequently, the difference in the equilibrium real wage under two different θ-realizations will also be independent of p.

2.3 Downward Rigidity at the Previous Period's Wage

I now turn to examine the implications of fairness preferences. Expression (2) indicates 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: $w_j = \overline{w}(\theta, p, \bar{w}_{t-1})\ \forall j$, where $\overline{w}(\theta, p, \bar{w}_{t-1})$ denotes the equilibrium wage level corresponding to total factor productivity (TFP) θ, price p, and the previous period's wage $\bar{w}_{t-1}$ in the fairness case. All firms demand the same amount of labor, $\overline{L}(\theta, p, \bar{w}_{t-1})$. For a given $\overline{w}$, this is pinned down by the firm's first order condition, which is discontinuous around $\bar{w}_{t-1}$:

$$\overline{w} = \begin{cases} p\theta f'\left(\overline{L}\right) & \overline{w} \geq \bar{w}_{t-1} \\ p\theta\lambda f'\left(\lambda\overline{L}\right) & \overline{w} < \bar{w}_{t-1} \end{cases}. \tag{5}$$

When $\overline{w} \geq \bar{w}_{t-1}$, this corresponds exactly to the first order condition in the benchmark case. However, when $\overline{w} < \bar{w}_{t-1}$, 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 $\lambda < 1$. This implies that at wages below $\bar{w}_{t-1}$, firms demand less labor than in the benchmark case. Note that this condition holds for many common production functions, such as Cobb-Douglas: $f(eL) = (eL)^{\alpha}$.

Implicitly define θ_R as:

$$w^*(\theta_R, p) = \bar{w}_{t-1}. \tag{6}$$

In other words, θ_R is the unique value of θ at which $\bar{w}_{t-1}$ would be the market clearing equilibrium wage. Proposition 1 establishes asymmetric wage adjustment around θ_R.

Proposition 1: Asymmetric adjustment to shocks

In the unique pure strategy symmetric Nash equilibrium:

(i) $\theta < \theta_R$: For a range of productivity realizations below θ_R, there will

be no downward wage adjustment. Wages will remain fixed at the previous period's wage and there will be excess supply of labor. Specifically, there exists a $\widetilde{\theta}_R < \theta_R$ *such that for all* $\theta \in \left(\widetilde{\theta}_R, \theta_R\right)$, $\overline{w}(\theta, p, \bar{w}_{t-1}) = \bar{w}_{t-1} > w^*(\theta, p)$. *In addition,* $\lim\limits_{\lambda \to 0} \widetilde{\theta}_R = 0$.

(ii) $\theta \geq \theta_R$*: For any productivity realization above* θ_R*, there will be upward wage adjustment. The equilibrium wage will correspond to the benchmark case and the labor market will clear:* $\overline{w}(\theta, p, \bar{w}_{t-1}) = w^*(\theta, p)$.

Proof: See Appendix B.2. ■

For values of θ above θ_R, firms will increase wages smoothly as θ rises. However, for sufficiently small decreases in θ below θ_R, it will be more profitable to maintain wages at $\bar{w}_{t-1}$ than to cut wages and have effort decreases due to worker retaliation. However, if θ falls below $\widetilde{\theta}_R$, $\bar{w}_{t-1}$ is no longer the unique equilibrium, and wages may fall below $\bar{w}_{t-1}$. Note that $\widetilde{\theta}_R$ will be lower for smaller values of λ: as λ approaches 0, firms will never find it profitable to lower wages below $\bar{w}_{t-1}$.

This contradicts Null hypothesis 1. Proposition 1 predicts that for any two $\theta', \theta'' \in \left(\widetilde{\theta}_R, \theta_R\right]$, the equilibrium wage will be the same: $\overline{w}(\theta', p, \bar{w}_{t-1}) = \overline{w}(\theta'', p, \bar{w}_{t-1})$.

2.4 Impact of Increases in the Previous Period's Wage

In the benchmark case, previous wages have no impact on period t wages. However, this will no longer be true when there is reference dependence around the previous period's wage. Compare the case of two different lagged wage levels: $\bar{w}_{t-1}^{low} < \bar{w}_{t-1}^{high}$. Following equation (6) above, define θ_R^{high} implicitly as $w^*\left(\theta_R^{high}, p\right) = \bar{w}_{t-1}^{high}$.

Proposition 2: Ratcheting: Effects of a higher lagged wage

(i) For any $\theta < \theta_R^{high}$ *and* λ *sufficiently small, the period* t *wage will be higher and employment will be lower if* $\bar{w}_{t-1} = \bar{w}_{t-1}^{high}$ than if $\bar{w}_{t-1} = \bar{w}_{t-1}^{low}$.

(ii) For any $\theta \geq \theta_R^{high}$*, the period* t *wage and employment levels will be the same under* $\bar{w}_{t-1}^{high}$ and $\bar{w}_{t-1}^{low}$.

Proof: See Appendix B.3. ■

A higher lagged wage has the potential to exacerbate distortions in the current period through two channels. First, there is a larger range of θ-values at which labor market distortions occur. Second, for any given θ where the rigidity binds, the higher lagged wage will constitute a larger departure from the market clearing level. In contrast, because the rigidity does not bind for $\theta \geq \theta_R^{high}$, the lagged wage—as long as it is weakly less than $\bar{w}_{t-1}^{high}$—is irrelevant. Note that Proposition 2 contradicts Null hypothesis 2.

2.5 Impact of Inflation

In the benchmark case, prices are neutral. This is no longer true when workers have fairness preferences over a nominal wage.

> **Proposition 3: Inflation will mitigate distortions from rigidity**
>
> *(i) For any fixed $\theta < \theta_R$ where the wage is distorted above the market clearing level so that $\overline{w}(\cdot) = \bar{w}_{t-1}$, an increase in price levels will lower the real wage: $\frac{\partial}{\partial p}\left(\frac{\overline{w}(\cdot)}{p}\right) < 0$. With sufficient inflation, $\bar{w}_{t-1}$ will equal the market clearing wage.*
>
> *(ii) For any $\theta \geq \theta_R$, an increase in price levels will have no effect on the real wage; nominal wages will rise to keep the real wage constant.*
>
> Proof: See Appendix B.4. ■

For any $\bar{w}_{t-1}$, a price increase means that the value of θ at which $\bar{w}_{t-1}$ is the market clearing nominal wage will now be lower; i.e., inflation lowers θ_R. Because the rigidity will bind to the left of this lower θ value, distortions will affect a smaller portion of the θ-distribution. Intuitively, inflation enables firms to achieve real wage reductions while keeping the nominal wage fixed at $\bar{w}_{t-1}$, thereby avoiding effort retaliation.

Proposition 3 contradicts Null hypothesis 3. Inflation lowers the real wage whenever the wage is distorted at the previous period's wage. This means that inflation undoes the asymmetric adjusment prediction under Proposition 1. Specifically, suppose $\theta' < \theta''$ but $\overline{w}(\theta', p, \bar{w}_{t-1}) = \overline{w}(\theta'', p, \bar{w}_{t-1})$. Then, as shown in the proof in Appendix B.4, there is a sufficiently high price level, p', where the market clears under both θ'

and θ''. Consequently, after a change in prices to p', $\overline{w}(\theta', p', \bar{w}_{t-1}) < \overline{w}(\theta'', p'', \bar{w}_{t-1})$. Similarly, inflation will also mitigate the distortion from high lagged wages in Proposition 2. Regardless of the value of θ, with a sufficient increase in prices, $\bar{w}_{t-1}$ will be less than the market clearing nominal wage in period t, so that the fairness norm becomes irrelevant and the rigidity does not bind.

2.6 Discussion

The model assumes that firms make decisions only taking into account current period payoffs. In a multi-period setting, if there is a high θ-realization, firms would trade off the benefits of raising wages to satisfy labor demand now, versus the expected decrease in future profits from the ratcheting effect. In the model, the former consideration would dominate the latter, producing almost full upward adjustment to positive shocks. This is because each firm gains the full benefit of posting a higher wage this period, but only bears a infinitesimal fraction of the cost since its wage contributes negligibly to the average market wage. In reality, a firm may internalize more of the future costs—e.g., if it has long-term relationships with individual workers or if firms can collude to not raise wages. However, the literature suggests that in the empirical context of this study, this is unlikely.[19] To the extent that this does occur, the core qualitative predictions that distinguish rigidity from the benchmark case above would still remain, but the expected magnitude of the effects would be smaller. This would make it less likely that I would be able to reject the null model in favor of downward nominal rigidity.

In addition, the model assumes the reference point is the previous period's nominal wage. Other formulations, such as the expected wage (Koszegi and Rabin 2006), would alter some of the specific predictions.[20] Alternately, consistent with Loewenstein and Prelec (1991), workers may demand upward sloping wage profiles. This could lead the

[19] For example, Dreze and Mukherjee (1989) observe, "No explicit collusion exists between either employers or labourers. Individual employers have no monopsonistic power: the pool of employers is large, and re-sorting of partners occurs constantly."

[20] For example, prior positive shocks would not necessarily create ratcheting because the reference point would depend on the expected value of θ. Inflation would not affect real wage adjustment if the reference point is formulated with respect to the real wage.

reference wage to be of the form $\bar{w}_{t-1}(1+\varphi)$, reflecting a norm for a φ percentage wage increase in each period. My formulation of the reference point is simple and matches the survey evidence provided in Section 6 and in Kahneman et al. (1986). While the empirical results below do appear to provide support for some types of reference points as being more likely than others, I take no strong stance on the functional form of the reference point, or on the micro-foundation for rigidity more generally.

3 Empirical Strategy

3.1 Context: Rural Labor Markets in India

Agricultural production in India, as in most developing countries, is largely undertaken on smallholder farms. The median household farm size is about 0.9 acres.[21] The composition of farm employment is often a mix of household and hired labor. Markets for hired labor are active: most households buy and/or sell labor.[22] Labor is typically traded in decentralized markets for casual daily workers. 98% of agricultural wage employment is through casual wage contracts (with regular/salaried workers making up the bulk of the remaining 2%). In addition, 67% of landless rural workers report casual employment as their primary source of earnings.

Within a village, there is typically a gender-specific prevailing wage for casual daily labor for any given task. This has been documented in earlier development work on India. For example, Dreze and Mukherjee (1989) state, "[I]n normal times a *single* wage rate applies to all adult males in the village for a 'normal' day's work, irrespective of the identity of the partners involved. If the task is of a special nature...some bargaining may take place." Similarly, Bliss and Stern (1982) note, "At any particular time everyone in the village knew what the going rate was. And in nearly every case that wage or something of equivalent value would be paid to every agricultural laborer."

Using more recent data, Figure 3 plots the distribution of casual daily wages re-

[21] Unless stated otherwise, the statistics in this sub-section are computed from India's National Sample Survey Employment/Unemployment rounds (1982-2009).

[22] See, for example, Rosenzweig (1980), Benjamin (1992), and Bardhan (1997).

ported by agricultural laborers. In the ICRISAT data (Panel A), workers were asked their average wage over the past year or season. Over 80% of workers within a village report the same exact wage. In the 0more detailed data collected by Breza, Kaur, and Shamdasani (BKS) (2017) in Orissa (Panel B), respondents reported their activity and wage for each day in the past ten days.[23] The reported daily wage is the same in about 80% of worker-day observations within a village. This supports the presumption that there is a salient prevailing wage at any given point in time. In addition, the prevailing agricultural wage (i.e. mode) stays the same over the one month study period in all villages in the BKS sample.

There are few formal 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 1-3 days).[24] 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 private wage labor market (Rosenzweig 1980; 1988).

Agricultural production is heavily rainfall dependent and exhibits considerable seasonality. The major rainfall episode is the yearly monsoon, which accounts for over 80% of annual rainfall. The monsoon arrives between May-July in most parts of the country and marks the beginning of the agricultural year. For rice (the major crop) as well as some other crops, planting occurs once the rains begin. Subsequent months involve various activities such as transplanting, fertilizer application, and weeding. Rice harvesting typically occurs between November and January. February-April is the lean season in rain-fed areas; during this time, growing crops usually requires irrigation and the monsoon is a less important determinant of labor demand.

[23]This data was collected from laborers who were not randomly selected to receive employment offers in their worksites. Consequently, the survey respondents were engaged in casual daily work in their villages during the study period.

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

3.2 Empirical Tests

A distinct labor market is defined as an Indian district (an administrative geographic unit). Let θ_{dt} denote the rainfall realization in district d in year t. The empirical implementation will focus on discrete shocks. As discussed in Section 3.4, in each year, a labor market can experience a negative shock (low rainfall), no shock (the usual level of rainfall), or a positive shock (high rainfall): $\theta_{dt} \in \left\{\theta^{Neg}, \theta^{Zero}, \theta^{Pos}\right\}$. I assume these shocks are i.i.d.: uncorrelated with any other determinants of the wage and serially uncorrelated across years. In addition, as in the model, I assume the shocks are transitory: rainfall in a given year affects TFP in only that year.[25]

In the absence of rigidities, the following simple model captures the effects of transitory shocks on equilibrium wages:

$$\ln w_{dt} = \alpha_0 + \alpha_1 Pos_{dt} + \alpha_2 Neg_{dt} + \ln p_t + \epsilon_{dt}, \tag{7}$$

where Pos_{dt} and Neg_{dt} are dummies for a positive and negative shock, respectively. α_1 and α_2 give the difference in the wage level under these shocks relative to the omitted category of $Zero_{dt}$. Null hypothesis 1 establishes that $\alpha_1 > 0$ and $\alpha_2 < 0$. In accordance with Null hypothesis 2, lagged values do not appear in equation (7) because they are irrelevant. Consistent with Null hypothesis 3, prices enter only additively: a price increase raises the nominal wage to keep the real wage constant. This means that, for example, the difference in wages between $Neg_{dt} = 1$ and $Zero_{dt} = 1$ is fixed at α_2; this difference is not affected by inflation. The empirical strategy builds on this basic specification, which is amenable to the fact that much of the analysis relies on data from repeated cross-sections over non-consecutive years.[26]

These null predictions will not hold in the presence of nominal rigidity. Proposition

[25] This is a standard assumption in prior work (e.g., Paxson 1992; Rosenzweig and Wolpin 1993; Townsend 1994; Jayachandran 2006). Below, I use the results to directly document lack of serial correlation in shocks, and to rule out persistent productivity impacts of shocks.

[26] Note that this equilibrium wage model can also be expressed in a first differences framework. It is straightforward to verify that writing equation (7) for $\ln w_{d,t-1}$ and subtracting from (7) gives: $\ln w_{dt} - \ln w_{d,t-1} = \alpha_1 \left(Pos_{dt} - Pos_{d,t-1}\right) + \alpha_2 \left(Neg_{dt} - Neg_{d,t-1}\right) + I_t + \xi_{dt}$, where $I_t \equiv \ln p_t - \ln p_{t-1}$ is the inflation level. The α_1 and α_2 coefficients have the same expected value in both specifications. However, equation (7) has the advantage that it does not require data from consecutive years.

1 predicts that in equation (7), $\alpha_2 = 0$ if inflation is sufficiently low. Proposition 2 can be tested by adding lagged values. Specifically, the expected value of $\bar{w}_{t-1}$ will be higher if there was a positive shock in year $t-1$. Proposition 2 (i) therefore implies that if $\theta_{d,t-1} = \theta^{Pos}$, then in year t, wage distortions can occur for any $\theta_{dt} < \theta^{Pos}$ (i.e., for θ^{Neg} and θ^{Zero}). Model (8) below expands equation (7) by adding dummies for a lagged positive shock, $Pos_{d,t-1}$, for the cases where $\theta_{dt} = \theta^{Neg}$ and $\theta_{dt} = \theta^{Zero}$. Thus, in order to enable separate tests of Propositions 1 and 2, the following specification breaks up the case of negative shocks into two subcases:

$$\begin{aligned}\ln w_{idt} \;=\; & \beta_0 + \beta_1 Pos_{dt} + \beta_2 NonPos_{d,t-1}Neg_{dt} + \beta_3 Pos_{d,t-1}Neg_{dt} + \beta_4 Pos_{d,t-1}Zero_{dt} \\ & + \textstyle\sum_{k=2}^{K} \phi_k \widetilde{P}os_{d,t-k} + \delta_{\mathbf{d}} + \rho_{\mathbf{t}} + \varepsilon_{idt},\end{aligned} \tag{8}$$

where where $NonPos_{d,t-1}$ is an indicator for a non-positive shock last year (i.e. $NonPos_{d,t-1} \equiv Zero_{d,t-1} + Neg_{d,t-1}$), $\rho_{\mathbf{t}}$ are year fixed effects (which absorb p_t), and δ_d are district fixed effects that capture differences in real wage levels across districts.

In principle, positive shocks in even earlier years, such as $t-2$, could distort current period wages; the power to detect these effects will be lower than from a positive shock in period $t-1$ because there is a longer period of time over which inflation can erode the ratcheting effect (see below). However, such earlier positive shocks could still weaken the sharpness of the tests of Propositions 1 and 2. To sharpen the predictions, the $\sum_{k=2}^{K} \widetilde{P}os_{d,t-k}$ covariate vector controls for a longer history of lagged positive shocks from periods $t-2$ to $t-K$. Specifically, $\widetilde{P}os_{d,t-k}$ is a binary indicator that equals 1 if there was a positive shock $t-k$ periods ago and no positive shock since then (i.e. from periods $t-k+1$ to period t), and equals 0 otherwise.[27] With these controls, the omitted shock category in model (8) is no shock this year, and non-positive shocks

[27]Specifically, these controls are defined as: $\widetilde{P}os_{d,t-k} \equiv Pos_{d,t-k} \prod_{m=t-k+1}^{t} (1 - Pos_{d,m})$. Under rigidities, prior high rainfall shock will only matter if it is not followed by high rainfall in a more recent year; otherwise the wage would adjust upward later anyway, making the older shock irrelevant. For this reason, I use these $\widetilde{P}os_{d,t-k}$ controls, rather than just dummies for $Pos_{d,t-k}$. This also increases power to detect effects on Pos_{dt} and $Pos_{d,t-1}$ in the specification. In practice, prior positive shocks often dissipate within a couple years. Note that it is not necessary to add similar controls for a longer history of lagged negative shocks; indeed, the inclusion of such controls makes essentially no difference to the results.

in the past K years. This means that there have been no upward perturbations in the past wage from high rainfall in earlier years. Consequently, the expected wage associated with the omitted category approximates the market clearing wage under no shock: $w^*(\theta^{Zero}, p)$.[28] In other words, with this specification, θ^{Zero} is a proxy for θ_R—setting up a direct test of the model's predictions. This approach allows me to maximize power for tests by focusing on shocks in periods $t-1$ and t, while creating a "clean" reference value for tests. In the analysis, I show the results with and without these controls.

Both Null hypothesis 1 and Proposition 1 predict $\beta_1 > 0$: wages should be higher when there is a positive shock than under no shock (the omitted category). Thus, outcomes under high rainfall states will not distinguish rigidities from full adjustment. β_2 provides a test of asymmetric adjustment. Null hypothesis 1 predicts $\beta_2 < 0$, while Proposition 1 predicts that $\beta_2 = 0$ (when inflation is sufficiently low). Note that the Null hypothesis 1 does not necessarily impose the restriction that $\beta_1 = -\beta_2$; this will depend on whether the TFP shock under θ^{Neg} and θ^{Pos} is of equal magnitude, relative to θ^{Zero}. To test for asymmetric adjustment, I therefore test Proposition 1 with the weaker assumption that $\theta^{Neg} < \theta^{Zero} < \theta^{Pos}$. If my weaker test fails, then this implies the more stringent restriction of $\beta_1 = -\beta_2$ will also fail.

The β_3 and β_4 coefficients provide tests of Proposition 2. Null hypothesis 2 predicts that $\beta_4 = 0$: this year's TFP is the same as the omitted category and so wages should be the same. However, under downward rigidities, the wage increase from last year's high rainfall would persist into the current year—keeping wages above $w^*(\theta^{Zero}, p)$. Proposition 2 therefore predicts that $\beta_4 > 0$: nominal wages will be higher due to the ratcheting effect. In addition, as was the case for β_2, under the null, $\beta_3 < 0$. However, Proposition 2 predicts that $\beta_3 > 0$: wages could be *higher* than the omitted category of no shock, even though there is a negative shock in year t.[29]

[28] Note that the validity of the empirical strategy does not rely on the wage level under the omitted category truly being the market clearing wage. Rather, what is important is that the omitted category captures the counterfactual for the wage under usual rainfall without any ratcheting effects (i.e. no upward distortions) from prior shocks.

[29] Note that model (8) does not include a separate test for the case of $Pos_{d,t-1}Pos_{dt}$. This is because

Finally, note that under the null of full adjustment, model (8) should reduce exactly to model (7): $\beta_1 = \alpha_1 > 0$; $\beta_2 = \beta_3 = \alpha_2 < 0$; and $\beta_4 = 0$. Thus, equation (8) will only have additional explanatory power if there are downward rigidities.

Proposition 3 predicts that, in the presence of rigidities, inflation will move wages closer to market clearing levels. I test this by interacting each of the shock categories with inflation:

$$\begin{aligned}\ln w_{idt} \;=\;& \gamma_0 \;+\; \gamma_1 Pos_{dt} \;+\; \gamma_2 NonPos_{d,t-1} Neg_{dt} \;+\; \gamma_3 Pos_{d,t-1} Neg_{dt} \;+\; \gamma_4 Pos_{d,t-1} Zero_{dt} \\ & + \psi_1 Pos_{dt} \times I_t \;+ \psi_2 NonPos_{d,t-1} Neg_{dt} \times I_t \;+ \psi_3 Pos_{d,t-1} Neg_{dt} \times I_t \\ & + \psi_4 Pos_{d,t-1} Zero_{dt} \times I_t \;+\; \textstyle\sum_{k=2}^{K} \phi_k \widetilde{P}os_{d,t-k} \;+\; \delta_{\mathbf{d}} \;+\; \rho_{\mathbf{t}} \;+\; \varepsilon_{idt}, \end{aligned} \tag{9}$$

where I_t is price inflation from $t-1$ to t. In this model, γ_1, γ_2, γ_3, and γ_4 capture the difference between the omitted category and each respective shock category when inflation is zero. They therefore provide a sharper test of Propositions 1-2, which predict $\gamma_1 > 0$, $\gamma_2 = 0$, $\gamma_3 > 0$, and $\gamma_4 > 0$. The coefficients on the interaction terms capture how each of these differences changes with inflation.

First, note that because the omitted category approximates $w^*(\theta^{Zero}, p)$, if price levels rise, the nominal wage in the omitted category will rise accordingly to maintain a constant real wage. The same will be true when $Pos_{dt} = 1$. Consequently, Null hypothesis 3 and Proposition 3(ii) both predict that $\psi_1 = 0$: the difference in nominal wages between Pos_{dt} and the omitted category will not change with inflation.

In contrast, inflation will not be neutral in the other shock cases, in which wages are distorted above market clearing levels. In these cases, employers can keep nominal wages fixed, enabling real wage reductions through inflation. Consequently, with inflation, nominal wages will end up being lower under $NonPos_{d,t-1}Neg_{dt}$ than the omitted category: $\psi_2 < 0$. Similarly, inflation will also mitigate the ratcheting effect, so that lagged transitiory positive shocks do not cause nominal wages to be higher than

under both the null and under rigidities (Proposition 2 (ii)), lagged high rainfall levels will not matter if the rainfall this year is also high. This sub-case is therefore subsumed under Pos_{dt}. In general, specification (8) expands model (7) to only include those sub-cases of shocks that can distinguish predictions under rigidity from the null. This keeps the main estimating equation parismonious. It also helps with statistical power. In the appendix below, I also show results for the full set of interactions between lagged and current rainfall levels, which constitute $3 \times 3 = 9$ cells.

the omitted category in year t: $\psi_3 < 0$ and $\psi_4 < 0$. In contrast, under Null hypothesis 3, $\psi_2 = \psi_3 = \psi_4 = 0$. This again means that under the null, specification (9) should reduce to specification (7).

In addition to providing a direct test of Proposition 3, specification (9) is helpful for two reasons. Model (8) pools across high and low inflation periods; it will therefore only have power to distinguish rigidities if average inflation across years is sufficiently low. Second and relatedly, in model (8), if $\beta_2 = 0$ but inflation is high (i.e. ρ_t is positive and large), then this could mean that nominal wages are rising in absolute terms despite a negative shock. Under the reference point assumed in Section 2—where workers dislike wage cuts, but do not demand consistent wage increases-–we would expect this to happen if inflation is high, but not if it is low. For both these reasons, the level effects on the shock covariates in model (9) are important because they isolate wage adjustment in periods of low inflation.

Finally, this empirical strategy allows a test for whether rigidities have real effects on employment. I replace the dependent variable in model (8) with e_{idt}—the employment level of worker i in district d in year t:

$$\begin{aligned} e_{idt} \;=\;& \sigma_0 + \sigma_1 Pos_{dt} + \sigma_2 NonPos_{d,t-1} Neg_{dt} + \sigma_3 Pos_{d,t-1} Neg_{dt} + \sigma_4 Pos_{d,t-1} Zero_{dt} \\ & + \textstyle\sum_{k=2}^{K} \phi_k \widetilde{P}os_{d,t-k} + \delta_{\mathbf{d}} + \rho_{\mathbf{t}} + \varepsilon_{idt}. \end{aligned} \tag{10}$$

Under both the Null hypotheses and Proposition 1, employment should rise with positive shocks and fall under negative shocks: $\sigma_1 > 0$ and $\sigma_2 < 0$.

Testing for employment distortions requires a counterfactual benchmark of what employment would be if wages could adjust downward. Proposition 2 enables such a test using lagged transitory positive shocks. Specifically, in the omitted category, there is no shock in the current year. This therefore serves as a counterfactual for what employment would be if wages could adjust down after the lagged high rainfall in the $Pos_{d,t-1}Zero_{dt}$ case. If the wage distortion from the ratcheting effect lowers employment, then $\sigma_4 < 0$. In contrast, under the null, $\sigma_4 = 0$. Similarly, Proposition 2 predicts that $\sigma_3 < \sigma_2$: $Pos_{d,t-1}Neg_{dt}$ will lead to lower employment than

$NonPos_{d,t-1}Neg_{dt}$, because of the additional wage distortion from ratcheting in the former case. In contrast, under the null, $\sigma_3 = \sigma_2$.[30]

It would also be interesting to test whether inflation mitigates employment distortions. However, because employment data is only available for a small number of years—providing little variation in inflation—it is not possible to examine differential employment effects by inflation (see below).

3.3 Data

Wage and employment data is constructed using two primary datasets. The first source is the rural sample of the Employment/Unemployment rounds of the Indian National Sample Survey (NSS), a nationally representative survey of over 600 Indian districts.[31] Households in each district are sampled on a rolling basis over the agricultural year (July to June). The survey elicits daily employment and wage information for each household member over the 7 days preceding the interview. The surveys were conducting during the 1982, 1983, 1987, 1993, 1999, 2003, 2004, 2005, 2007, and 2009 agricultural years.[32] The second source is the World Bank Agriculture and Climate dataset, which provides yearly data on 240 Indian districts in 13 states from 1956-1987. The unit of observation is a district-year. Rainfall data is taken from *Terrestrial Precipitation: 1900-2008 Gridded Monthly Time Series* (version 2.01), constructed by the Center for Climatic Research, University of Delaware. Appendix C provides further details on data construction, and Appendix Table 1 provides summary statistics.

3.4 Definition of Shocks

I focus on rainfall in the first month when the monsoon typically arrives in a district (which ranges from May to July). Focusing on rain in the month of expected arrival

[30]The model also predicts labor rationing under $NonPos_{d,t-1}Neg_{dt}$, but in this case, there is no clear counterfactual for what employment levels would be if wages were flexible.

[31]A district is an administrative unit in India (like counties in the US). On average, there are 17 districts per state and approximately 2 million residents per district.

[32]Since the monsoon is the rainfall shock used in the analysis, the results will focus on wages and employment between the month of monsoon arrival and the end of harvesting in January.

reflects the fact that both the level of rain and the timeliness of its arrival are important determinants of productivity. To construct shocks, I compute the rainfall distribution for each district separately for each dataset: for the years 1956-1987 for the World Bank data and the years 1982-2009 for the NSS data. A shock is a deviation in rainfall from a district's usual rainfall level. Specifically, as in Jayachandran (2006), a positive shock is rainfall above the eightieth percentile for the district and a negative shock is rainfall below the twentieth percentile. These discrete cut-offs capture the non-linear relationship between rainfall and productivity and increase power. This illustrated in Appendix Figure 1: rainfall in the upper (lower) tail of the distribution is associated with increased (decreased) yields, while the middle of the rainfall distribution has a relatively flat relationship with yields.

Rainfall is serially uncorrelated across years (Appendix Table 2). To allow for the possibility of correlated shocks across districts in a given year, standard errors are clustered by region-year in all regressions, using the region definitions from the NSS.[33]

4 Results

4.1 Test for Wage Adjustment

Table 1 provides a preliminary test for wage adjustment (as in model (7)), showing results from the World Bank and NSS datasets side by side. The dependent variable is the log nominal daily wage for agricultural work.[34] In both datasets, relative to no shock, nominal wages adjust up when there are positive shocks, but I cannot reject that they are not lower on average when there is a negative shock (Cols. 1 and 4).[35] In Cols. 2 and 5, there is some evidence that a positive shock in one year leads to a persistent increase in wages in the following year. Under rigidities, a lagged positive

[33] Appendix Table 2 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.

[34] The World Bank data provides the average daily cash wage in each district-year. In the NSS data, I compute the daily agricultural wage as total (cash plus in-kind) value of paid earnings for casual agricultural work divided by days worked over the past 7 days. See Appendix C for more details.

[35] Below, I show that employment does indeed fall sharply when there are negative shocks.

shock has the potential to distort wages upward particularly if the current year's shock is none or negative. If the current shock is positive, wages would need to adjust up anyway, rendering the prior positive shock irrelevant. Cols. 3 and 6 limit analysis to non-positive shocks in the current year—as expected, this increases the magnitude of the coefficients and lagged positive shocks significantly raise current wages (relative to having no shock last year) in both datasets. In contrast, consistent with rigidity in the downward direction, lagged negative shocks have no persistent wage effects.

Table 2 shows the full test corresponding to specification (8). Cols. 1-2 examine effects in the World Bank data. In Col. 2, relative to the counterfactual of no shock this year and no shock last year, wages are 4.3% higher if there is positive shock this year (row 1, significant at the 1% level). In contrast, consistent with Proposition 1, wages are not significantly lower if there is a negative shock this year: while β_2 has a negative sign, it is small in magnitude and I cannot reject that it is zero (row 2), and β_3 is actually positive (row 3).[36] In addition, consistent with Proposition 2, lagged positive shocks have persistent wage effects (rows 3 and 4). For example, when there is a positive shock last year and no shock this year, wages are 3.7% higher on average than if last year's positive shock had not occurred (significant at the 1% level). The pattern of findings is similar in the NSS data (Cols. 3-4). Col. 5 limits analysis to individuals whose primary source of earnings is casual daily labor, with similar results. Col. 6 adds controls for individual covariates and season of the year. Women earn substantially less than men, but landholdings and education have no predictive power for wages.[37]

I provide a series of robustness checks in the Apendix Tables. The finding of wage rigidity holds separately for each gender (Appendix Table 5), is robust to limiting analysis to the cash component of the wage (Appendix Table 6), and appears stronger for

[36] In addition, I reject that $\beta_1 = -\beta_2$ in both the World Bank data (p-value=0.043) and NSS data (p-value=0.011). However, as discussed in Section 3.2, this null hypothesis requires stronger assumptions about the production function.

[37] Appendix Table 3 shows the raw wage change patterns for each shock category using the World Bank data. The results on wage change premiums are consistent with the findings in Table 2. Appendix Table 4 runs a more detailed version of the main specification in Table 2, with each of the 9 shock sequences estimated separately.

flat wages relative to piece rate contracts (though the test is under-powered, Appendix Table 7). In addition, Appendix Tables 8-9 show robustness of these and subsequent results to alternative percentile cut-offs for defining positive and negative shocks.

4.2 Impact of Inflation on Wage Adjustment

To test Proposition 3, I use the World Bank data since it covers 32 years, providing substantial variation in inflation. (The NSS rounds are comprised of 8 years of data, with limited variation in inflation). Inflation is computed from the state-wise *Consumer Price Index for Agricultural Labourers in India*, published by the Government of India. For each district, I construct inflation as the average of inflation in all states excluding the district's own state. This captures the component of inflation that is nationally determined (by factors outside the district's own state) and therefore unaffected by local idiosyncratic shocks. Appendix Table 10 verifies that the district rainfall shocks have no correlation with prices in other states (Cols. 3-4) or inflation in other states (Col. 5)—the coefficients are small in magnitude and insignificant. The correlation between own state inflation and national inflation is 0.70.

Table 3, Cols. 1-2 present estimates of model (9), with interactions of each shock category with the continuous inflation rate in other states. Contemporaneous positive shocks increase wages (row 1). Consistent with Proposition 3(ii), there are no differential effects by inflation (row 2). When there are contemporaneous droughts, estimated wages are the same on average as the omitted category when inflation is zero (row 3). However, when there is positive inflation, nominal (and real) wages are lower under negative shocks than when there is no shock (row 4). Similarly, after lagged positive shocks, wages are ratcheted upwards when inflation is low (rows 5 and 7); as inflation rises, such shocks are less likely to have persistent effects on current wages (rows 6 and 8). Overall, the negative coefficients on the interaction terms in rows 4, 6, and 8 violate Null hypothesis 3 and are consistent with Proposition 3(i).

In Table 3, Cols. 3-4, the interaction term is a binary indicator for inflation above 6%—about the mean inflation rate in the sample. The pattern of results is similar.

Inflation has no differential effects when there are positive shocks, but does enable downward real wage adjustment in the three categories of shocks where rigidity creates distortions. As indicated in the F-test p-values at the bottom of the table, when inflation is above 6%: real wages adjust downward when there are negative shocks (significant at the 5% level) and I cannot reject that lagged positive shocks have no effect on current wages.

A potential concern is that there could be co-trends in inflation and the impact of rainfall shocks. For example, if inflation and the adoption of irrigation (which makes crops less reliant on rainfall) both trend upward over time, this could create a spurious correlation. In Appendix Table 11, I conduct two placebo tests to rule out this concern: interactions of the rainfall shocks with a linear time trend (Col. 2) and with a dummy for whether the year is after 1970 (the sample mid-point and the beginning of India's green revolution, Col. 3) are small and insignificant, indicating that the inflation results are not driven by co-trends.

4.3 Employment Effects

I test for employment effects on all individuals who comprise the potential agricultural labor force: rural workers for whom casual employment or self-employment (i.e. work on their own farm) is a primary or subsidiary activity. 100% of the individuals in the data who report any positive agricultural work fall within this group. Appendix Table 14 verifies that rainfall does not affect the composition of the sample—e.g., through the likelihood of reporting oneself as being in the agricultural labor force (Col. 1).

Employment in agriculture is the number of worker-days in the last 7 days (the interview reference period) in which the individual did any agricultural work: own farm work plus hired work on someone else's farm.[38] Table 4, Panel A indicates that, on average, a positive shock in the previous year lowers agricultural employment in

[38]Only 31% of the individuals in the potential agricultural labor force report doing any agricultural work (on their own land or for someone else) in the past week. Among these individuals, 66% of worker-days were comprised of work on one's own land, and the remaining were for work on someone else's land. Note that wages can only be measured for this latter group.

the current year. The estimated decrease in agricultural activity is 0.153 days/week or 8.8% for the average worker (Col. 2) and 0.193 days/week or 11% for landless laborers (Col. 3); these coefficients are significant at the 1% level.

Panel B shows the main specification, equation (10). Contemporaneous positive shocks (row 1) raise average employment by 0.145 days/week or 8.3%. Contemporaneous droughts (row 3) decrease employment by 0.094 days/week or 5.4%. Consistent with the prediction under rigidity, when a drought is preceded by a positive shock (row 5), employment drops by about 0.254 days/week or 14.6%—more than twice the magnitude of the decrease in row 3. This difference is statistically significant at the 10% level in Col. 1 and at the 5% level in Col. 2 (see bottom of table). Similarly, when a year in which there is no shock is preceded by a lagged positive shock (row 7), this lowers employment by 6-7%.

In village labor markets, those who own land have the right to use their own labor on their farms before hiring others. As a result, those with little or no land—who are the net suppliers to the casual daily labor market—are the most likely to be rationed when rigidities bind. Consistent with this, employment decreases are concentrated among those with less land (Col. 3). Finally, there is little evidence that the shocks affect hiring in the non-agricultural sector (Col. 4).

4.4 Separation Failures: Compositional Effects on Employment

A long theoretical literature has pointed out that labor rationing may affect the allocation of labor across firms (Singh, Squire, and Strauss 1986; Benjamin 1992). Specifically, a rationed household's decision of how much labor to supply and its decision of how much labor to use in production are no longer separable. Households with smaller landholdings—which are more likely to face a binding rationing constraint since they are more reliant on selling labor in the external market—will supply labor more intensively to their own farms. This will lead to a misallocation of labor, with more labor per acre used in small farms compared to large farms.

In Table 5, I test whether rationing affects the composition of labor supply for agricultural households. I examine effects separately for three groups, defined in terms of acres per adult in the household:[39] the landless, who have no or marginal land (<0.01 acres); below median landholding; and above median landholding. I limit analysis to observations in which there was a non-positive shock in the current year, since this is when lagged positive shocks will be most likely to generate rationing.

The dependent variable Col 1. is total worker-days in agriculture—the same measure as in Table 4. Consistent with the Table 4 results, agricultural employment among the landless drops substantially. On average, there is no effect on households with below median landholdings; however, this masks substantial changes in labor allocation for these small landholders. Col. 2 examines effects on hired labor on others' farms. In the year after a positive shock, while the landless experience the largest decrease in wage employment (1.198 days/week), small landholders also experience an estimated decrease of 0.444 days/week or 22% (significant at the 5% level). Col. 3 indicates that, at the same time, small landholders increase the amount of time spent working on their own farms by 0.449 days/week or 18%, significant at the 5% level—this is the key prediction of the separation failures framework. This magnitude corresponds to having approximately one extra acre of land (the sample median) in a typical year. In contrast, large landowners' labor supply is largely unaffected by lagged positive shocks; this makes sense since these households do not sell much labor externally.

5 Alternate Explanations

Could the results be explained by reasons other than downward nominal wage rigidity?

First, positive rainfall shocks may have persistent effects on productivity—for example by improving future soil moisture. However, then future employment should also be higher and inflation should not affect persistence, which contradicts the results.

[39] Acres per adult proxies for how much "excess" labor the household would traditionally supply off its own farm. This is consistent with traditional tests for separation failures, which examine whether, for a given number of acres, households with more adults tend to use more labor on their own farms (e.g., Benjamin 1992, Shapiro 1990, Udry 1996, LaFave and Thomas 2016). Note that I conduct this analysis at the household-year level to remain consistent with the previous literature.

Second, shocks may affect worker quality. During negative shocks, employers may hire the subset of workers who are better quality—leading to a higher average wage per worker. However, this should not depend on inflation. It also cannot explain why wages do not adjust back down after lagged positive shocks have dissipated. In addition, I find little evidence that the various shocks change the composition of who receives wage employment, in terms of gender, education, age, or wealth (Appendix Table 18).

Third, if positive shocks reduce future labor supply—e.g. through out-migration or inter-temporal substitution of labor—this could explain why wages rise and employment falls in the following year. However, to explain the lack of downward wage adjustment, this would need to (i) occur both in the year after a positive shock and during a contemporaneous drought and (ii) occur when inflation is low but not when it is high. It is unclear why labor supply shifters would operate in this way. In addition, there is no evidence of increased migration after lagged positive shocks or during contemporaneous negative shocks in the NSS data (Appendix Table 14) or in the ICRISAT data (Appendix Table 16).

Fourth, if positive shocks enable credit-constrained small farmers to invest in capital, this could decrease future labor demand. To fit the results in Table 6, capital would need to be complementary with own household labor (to explain the increase in own farm labor supply) and substitutable with hired labor (to explain the large decrease in hired labor). In this case, wages for hired manual labor should be lower after a lagged positive shock, not higher. In addition, it is unclear why these effects would occur only when inflation is low. This explanation also doesn't account for why downward wage adjustment is hindered during negative shocks, again only when inflation is low. Finally, there is little direct evidence that lagged positive shocks lead to an increase in bullocks, tractors, or fertilizer—among the most common and important capital inputs in this setting (Appendix Table 19).

Fifth, measurement error (e.g. due to rounding) is unlikely to drive the results. It is unclear why respondents would be differentially more likely to round wages during negative shocks and the year after positive shocks. In addition, if the wage results simply reflect reporting errors, we should not observe real employment effects.

Overall, the above arguments are of course suggestive. It is perfectly plausible that rainfall could affect labor supply or demand through a variety of channels. A complete investigation of their role is outside the scope of this paper. The model in this paper delivers a rich set of positive predictions under wage rigidity. The full pattern of results—for wages, employment, and inflation, along with asymmetry in effects for each of these tests—is consistent with these predictions.

Finally, efficiency wage models that do not involve nominal rigidities—such as moral hazard, screening, labor turnover, or nutrition—also generate equilibrium unemployment. However, they do not predict that wages will be rigid in response to shocks. For example, none of these models can account for why wages would rise under a positive shock but then not adjust back down 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 nominal rigidity. Other models of unemployment—such as implicit insurance, informal unions, or the fairness efficiency wage model presented in Section 2—could be consistent with these results if contracting pertains (at least in part) to the *nominal* wage. In this paper, I do not take a strong stance on the micro-foundation for rigidity, but rather argue that a model would need to incorporate some degree of nominal rigidity to explain the above findings.

6 Mechanisms: Survey Evidence on Fairness Norms

The presence of rigidities in markets for casual daily labor is perhaps especially surprising given the lack of institutional constraints in these markets. This suggests that non-institutional mechanisms discussed in the literature—such fairness norms against wage cuts—may play a role in maintaining rigid wages. To obtain suggestive evidence on the relevance of fairness considerations, I surveyed in 196 agricultural laborers and 200 employers in 34 villages across 6 districts in the Indian states of Orissa and Madhya

Pradesh.[40] Following Kahneman, Knetsch, and Thaler (1986), I presented scenarios about wage setting behavior and asked respondents to rate them as "Very fair", "Fair", "Unfair", or "Very unfair". Table 6 presents the scenarios and results.[41]

Panel A establishes baseline norms relating to wage cuts in 2 sets of situations. For example, question 1 presents a scenario in which a farmer who used to pay Rs. 120/day lowers the wage after a surge in unemployment after a factory (which used to pay Rs. 100/day) shuts down. The majority of respondents believed it was unfair if the farmer then re-hires a previous employee at Rs. 100 (62%) or if he hires one of the newly unemployed factory workers at Rs. 100 (55%).[42]

Panel B investigates whether norms are anchored on the nominal wage rather than the real wage. Question 3 presents scenarios that involve a 5% real wage cut due to a drought, but vary the level of the nominal wage change. 64% of respondents view a 5% nominal wage cut as unfair. However, if there is 5% inflation and no nominal wage change, 38% view it as unfair. If there is 10% inflation and a 5% nominal wage increase, the percentage viewing this as unfair drops to 9%.[43] Note that similar exercises in the US and Canada have produced similar patterns, with respondents exhibiting some (albeit a lesser) degree of "money illusion" (Kahneman et al. 1986; Shafir et al. 1997). Similarly, 29% of respondents view a real wage cut as unfair if it is achieved by reducing an in-kind payment of lunch. This is sharply lower than the reactions to a nominal wage cut of smaller magnitude in Scenario 3A.[44]

Panel C indicates that several wage setting behaviors associated with market clearing are at odds with expressed fairness norms. For example, 61% of respondents felt

[40]Orissa is one of India's poorest states, and is dominated by rain-fed paddy. Madhya Pradesh is more affluent, and a large portion of the survey areas is covered by soybeans, a cash crop.

[41]Each respondent was asked half the questions to prevent the survey from becoming tedious, and in the case of paired scenarios (1A/1B, 3A/3C, and 9A/9B), was asked only 1 version of the scenario.

[42]In this setting, it is common for some local factories to hire casual daily laborers from surrounding villages, drawing from the same labor pool as agricultural employers.

[43]In the local vernacular, the term "price of food and clothing" is used to describe inflation. Workers and employers say that this is frequently cited by workers when they are negotiating wages.

[44]Based on field interviews, the value of the food, when it is provided, usually exceeds Rs. 10. The responses to Scenario 3A vs. 4 are consistent with evidence that there is lower earnings rigidity (and fewer layoffs during recessions) of workers who receive a base salary plus a bonus, presumably because bonuses can be more easily cut during downturns (e.g. Kahn 1997).

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). 63% of respondents think it is unfair for an employer to raise the wage during a period of high labor demand to attract enough workers, and then lower the wage to its previous level in later weeks when demand is lower (Question 7).

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. If the job is offered at the prevailing wage (which would uphold fairness norms and possibly also show benevolence given the laborer's distress), 55% percent of respondents say the worker would exert more effort than usual and only 1% state he would exert less effort than usual. In sharp contrast, if the wage is below the prevailing rate, only 6% of respondents state the worker would exert extra effort, while 40% state the worker would exert less effort than usual. Responses to this question were not substantially different between workers and employers.

Of course, survey responses may not reflect the actual actions people take when the stakes are real. The pattern of results in Table 6 simply lends some plausibility to the idea that fairness norms may be a way in which rigid wages are maintained in village labor markets. It is unclear, however, whether such fairness preferences are inherent features of utility or whether they arise endogenously—for example, as a coordinating device among laborers in the presence of incomplete contracting.

Appendix Table 20 tabulates responses to supplementary questions about respondents' own experiences and behavior. For example, 100% of workers and employers state that in their memory, there has not been a single year during which the prevailing nominal agricultural wage for a given season was lower than that in the previous year (Questions 1 and 6).[45] 74% of laborers report having been involuntarily unemployed in the past (Question 2), and 95% of employers claim that they have never hired a

[45]During informal interviews, respondents stated that wages do vary within a year based on the season/tasks—for example, the transplanting, weeding, harvesting, and lean seasons may each have a distinct wage. They stated that the wage for each season takes as a starting ("reference") point the wage during that season in the previous year.

worker at a wage below the prevailing wage during the lean season (Question 8).

7 Conclusion

This paper tests for downward nominal wage rigidity in markets for casual daily agricultural labor. First, there is asymmetric wage adjustment: nominal wages rise in response to positive shocks but do not fall during negative shocks. 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, creating boom and bust cycles: employment is 9% lower in the year after a transitory positive shock than if the positive shock had not occurred. Fifth, consistent with the misallocation of labor across farms, households with small landholdings increase labor supply to their own farms when they are rationed out of the external labor market.

In addition to its broad implications for unemployment and business cycle dynamics, wage rigidity has particular relevance for developing country labor markets. One focus of the development literature has been that shocks cause shifts in the production frontier, leading to volatility in income and consumption. 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 fully in each period. As implied by the employment results, this means rigidities may lower the levels and further increase the volatility of output and income. In addition, the evidence indicates that landless and marginal farmers—who are the poorest and most vulnerable workers in this setting—bear the brunt of the labor market effects. The findings in Section 4.4 suggest that this has not only distributional consequences—it can impact labor (mis)allocation, and consequently is another channel by which rigidities affect aggregate output.

Finding rigidities in casual daily labor markets is perhaps surprising, given the lack of formal institutional constraints in this setting. The survey evidence suggests that agricultural workers and employers view nominal wage cuts as unfair and believe that they cause effort reductions. Fairness preferences against wage cuts have been expressed in a range of contexts, including in richer countries (e.g., Kahneman, Knetsch, and Thaler 1986). While the strength of the norms expressed in Table 6 appears somewhat higher than that expressed in OECD countries, the survey findings suggest the potential for some commonality in the reasons for rigidity across settings.

However, it is unclear whether such fairness preferences are inherent features of utility or whether they arise endogenously. For example, fairness norms may simply be a coordinating device among workers in a setting where formal contracting or unions are difficult. Further exploration of the microfoundations for fairness norms is necessary to fully assess the efficiency and welfare implications of wage rigidity. This in turn, would inform our understanding of why wage rigidity may appear more prevalent in some settings than in others.

References

1. Akerlof, George. 2002. "Nobel Lecture: Behavioral Macroeconomics and Macroeconomic Behavior." *American Economic Review.*
2. Akerlof, George, William Dickens, George Perry. 1996. "The Macroeconomics of Low Inflation." *Brookings Papers on Economic Activity.* 1: 1-76.
3. Akerlof, George, and Janet Yellen. 1990. "The Fair Wage-Effort Hypothesis and Unemployment," *Quarterly Journal of Economics.* 255-83.
4. Altonji, Joseph and Paul Devereux. 2000. "The Extent and Consequences of Downward Nominal Wage Rigidity." *Research in Labor Economics.* 19: 383-431.
5. Bardhan, Pranab. 1973. "Size, Productivity, and Returns to Scale: An Analysis of Farm-level Data in Indian Agriculture." *Journal of Political Economy.* 81(6).
6. Barattieri, Alessandro, Susanto Basu, and Peter Gottschalk. 2014. "Some Evidence on the Importance of Sticky Wages." *AEJ: Macroeconomics.*
7. Behrman, Jere. 1999. "Labor Markets in Developing Countries," in ed. O. Ashen-

felter and D. Card. (eds), *Handbook of Labor Economics*, Vol 3: 2859-2939.

8. Benjamin, Dwayne. 1992. "Household Composition, Labor Markets, and Labor Demand: Testing for Separation in Agricultural Household Models." *Econometrica.*
9. Benjamin, Daniel. 2015. "A Theory of Fairness in Labour Markets." The Japanese Economic Review. 66(2): 182-225.
10. Bewley, Truman F. 1999. *Why Wages Don't Fall During a Recession.*
11. Blanchard, Olivier. 1990. "Why Does Money Affect Output? A Survey", in Ben Friedman and Frank Hahn, editors, *Handbook of Monetary Economics.* Vol 2.
12. Blinder, Alan and Don Choi. 1990. "A Shred of Evidence on Theories of Wage Stickiness." *Quarterly Journal of Economics*, pp. 1003-1015.
13. Bliss, Christopher and Nicholas Stern. 1982. *Palanpur: The Economy of an Indian Village.* OUP Catalogue.
14. Breza, Emily, Supreet Kaur, and Yogita Shamdasani. 2017. "The Morale Effects of Pay Inequality." NBER Working Paper No. 22491.
15. Bryan, Gharad, Shyamal Chowdhury, and A. Mushfiq Mobarak. 2014. "Under-Investment in a Profitable Technology: The Case of Seasonal Migration in Bangladesh," *Econometrica.* 82(5): 1671-1748.
16. Card, David. 1990. "Unexpected Inflation, Real Wages, and Employment Determination in Union Contracts." *American Economic Review.*
17. Card, David and Dean Hyslop. 1997. "Does Inflation 'Grease the Wheels of the Labor Market'?", Romer and Romer, *Reducing Inflation: Motivation and Strategy.*
18. Clarida, Richard, Jordi Galì, and Mark Gertler. 1999. "The Science of Monetary Policy: A New Keynesian Perspective." *Journal of Economic Literature.* 37.
19. Dickens, William et al. 2007. "How Wages Change: Micro Evidence from the International Wage Flexibility Project." Journal of Economic Perspectives. 21(2).
20. Dreze, Jean and Anindita Mukherjee. 1989. "Labour Contracts in Rural India: Theories and Evidence." *The Balance Between Industry and Agriculture in Economic Development.* Palgrave Macmillan UK. pp. 233-265.
21. Ehrlich, Gabriel and Joshua Montes. 2015. "Wage Rigidity and Employment Out-

comes: Evidence from Administrative Data." Mimeo, University of Michigan.

22. Eliaz, Kfir and Ran Spiegler. 2013. "Reference Dependence and Labor-Market Fluctuations." *NBER Macroeconomics Annual*. Vol. 28.
23. Elsby, Michael. 2009. "Evaluating the Economic Significance of Downward Nominal Wage Rigidity." *Journal of Monetary Economics.* 56.2: 154-169.
24. Elsby, Michael, Donggyun Shin, and Gary Solon. 2016. "Wage Adjustment in the Great Recession and Other Downturns: Evidence from the United States and Great Britain." *Journal of Labor Economics.* 34.S1: S249-S291.
25. Fallick, Bruce, Michael Lettau, and William Wascher. 2016. "Downward Nominal Wage Rigidity in the United States During and After the Great Recession." Mimeo, Federal Reserve Board.
26. Fehr, Ernst, Lorenz Goette, and Christian Zehnder. 2009. "A Behavioral Account of the Labor Market: The Role of Fairness Concerns." *Annual Review of Economics*.
27. Fink, Gunther, B. Kelsey Jack, and Felix Masiye. 2014. "Seasonal Credit Constraints and Agricultural Labor Supply." NBER Working Paper 20218.
28. Galì, Jordi. 2009. *Monetary Policy, Inflation, and the Business Cycle: An Introduction to the New Keynesian Framework*. Princeton University Press.
29. Goldberg, Jessica. 2016. "Kwacha Gonna Do? Experimental Evidence about Labor Supply in Rural Malawi." *American Economic Journal: Applied Economics.*
30. Greenwald, Bruce and Joseph Stiglitz. 1987. "Keynesian, New Keynesian and New Classical Economics." *Oxford Economic Papers.* 39(1): 119-133.
31. Hall, Robert and Paul Milgrom. 2008. "The Limited Influence of Unemployment on the Wage Bargain." *American Economic Review.* 98(4): 1653-1674.
32. Holzer, Harry and Edward Montgomery. 1993. "Asymmetries and Rigidities in Wage Adjustments by Firms." *Review of Economics and Statistics.* 75(3).
33. Imbert, Clement and John Papp. 2015. "Labor Market Effects of Social Programs: Evidence from India's Employment Guarantee." *American Economic Journal: Applied Economics.* 7(2): 233-263.
34. Jayachandran, Seema. 2006. "Selling Labor Low: Wage Responses to Productivity

Shocks in Developing Countries." *Journal of Political Economy*. 114(3).

35. Kahn, Shulamit. 1997. "Evidence of Nomninal Wage Stickiness from Microdata." *American Economic Review*. 87(5).
36. Kahneman, Daniel, Jack Knetsch, and Richard Thaler. 1986. "Fairness as a Constraint on Profit Seeking: Entitlements in the Market." *American Economic Review*.
37. Koszegi, Botond and Matthew Rabin. 2006. "A Model of Reference-Dependent Preferences." *Quarterly Journal of Economics*. 121(4): 1133-1166.
38. LaFave, Dan and Duncan Thomas. 2016. "Farms, Families and Markets: New Evidence on Completeness of Markets in Agricultural Settings." *Econometrica*. 84(5):1917-60.
39. Lewis, W. Arthur. 1954. "Economic Development with Unlimited Supplies of Labour." *The Manchester School*. 22(2): 139–191.
40. Leibenstein, Harvey. 1957. *Economic Backwardness and Economic Growth*.
41. Loewenstein, George and Drazen Prelec. 1991. "Negative Time Preference." *American Economic Review Papers and Proceedings*. 81(2): 347-352.
42. Martins, Pedro, Gary Solon, and Jonathan Thomas. 2012. "Measuring What Employers Do about Entry Wages over the Business Cycle: A New Approach." *American Economic Journal: Macroeconomics*. 4.4: 36-55.
43. McKenzie, David, Caroline Theoharides, and Dean Yang. 2014. "Distortions in the International Migrant Labor Market." *American Economic Journal: Applied Economics*. 6(2): 49-75.
44. McLaughlin, Kenneth. 1994. "Rigid Wages?" *Journal of Monetary Economics*.
45. Mobarak, Mushfiq and Mark Rosenzweig. 2014. "Risk, Insurance and Wages in General Equilibrium." NBER Working Paper No. 19811.
46. Morten, Melanie. 2016. "Temporary Migration and Endogenous Risk Sharing in Village India." NBER Working Paper No. 22159.
47. Muralidharan, Karthik, Paul Niehaus, and Sandip Sukhtankar. 2016. "General Equilibrium Effects of (Improving) Public Employment Programs: Experimental Evidence from India." Mimeo, UC San Diego.

48. Paxson, Christina. 1992. "Using Weather Variability to Estimate the Response of Savings to Transitory Income in Thailand." *American Economic Review.* 82(1).
49. Pissarides, Christopher. 2009. "The Unemployment Volatility Puzzle: Is Wage Stickiness the Answer?" *Econometrica.* 77(5): 1339–1369.
50. Pitt Mark and Mark Rosenzweig. 1986. "Agricultural Prices, Food Consumption and the Health and Productivity of Farmers", in *Agricultural Household Models: Extensions, Applications, and Policy*, pp. 153-182.
51. Rogerson, Richard and Robert Shimer. 2011. "Search in Macroeconomic Models of the Labor Market", in Card and Ashenfelter (eds.), *Handbook of Labor Economics.*
52. Rosenstein-Rodan, P. N. 1956. "Disguised Unemployment and Under-employment in Agriculture." *Working Papers Series C*, Center for International Studies, MIT.
53. Rosenzweig, Mark. 1980. "Neoclassical Theory and the Optimizing Peasant: An Econometric Analysis of Market Family Labour Supply in Developing Countries." *Quarterly Journal of Economics.* (94): 31–56.
54. Rosenzweig, Mark. 1988. "Labour Markets in Low-income Countries", in H. Chenery and T. N. Srinivasan (eds), *Handbook of Development Economics.*
55. Schmitt-Grohé, Stephanie and Martín Uribe. 2013. "Downward Nominal Wage Rigidity and the Case for Temporary Inflation in the Eurozone." *Journal of Economic Perspectives.* 27(3): 193–212.
56. Shafir, Eldar, Peter Diamond, and Amos Tversky. 1997. "Money Illusion." *Quarterly Journal of Economics.* 112(2): 341-374.
57. Shapiro, Charles and Joseph Stiglitz. 1984. "Equilibrium Unemployment as a Worker Discipline Device." *American Economic Review.* 74(3): 433-444.
58. Singh, I., L. Squire and J. Strauss, eds. 1986. *Agricultural Household Models: Extensions, Applications, and Policy.* The World Bank, Washington, DC.
59. Tobin, James. 1972. "Inflation and Unemployment." *American Economic Review.*
60. Townsend, Robert. 1994. "Risk and Insurance in Village India." *Econometrica.*
61. Udry, Chris. 1996. "Efficiency and Market Structure: Testing for Profit Maximization in African Agriculture." Mimeo. Northwestern University.

62. Verdugo, Gregory. 2016. "Real Wage Cyclicality in the Eurozone Before and During the Great Recession: Evidence from Micro Data." *European Economic Review*. 82: 46-69.

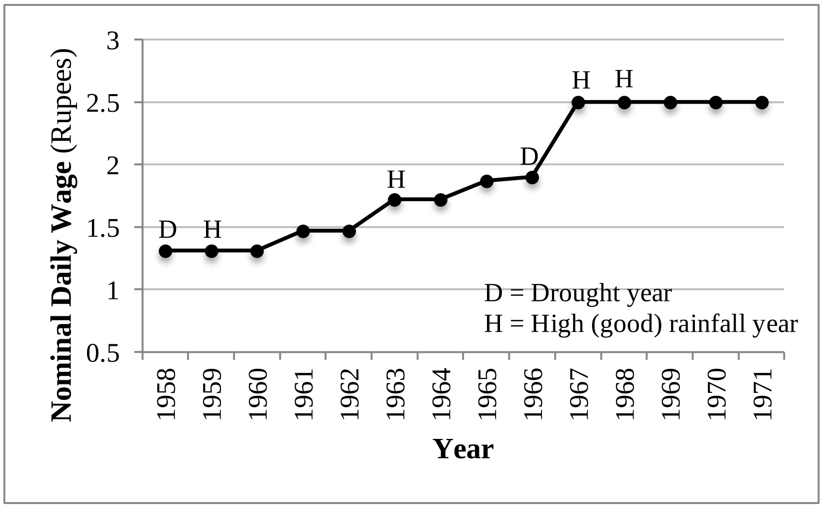


Figure 1 – Evolution of the Prevailing Nominal Daily Wage in an Indian Village

Notes:

1. This motivational figure plots the prevailing daily nominal wage for ploughing in the Indian village of Tinur, Tamil Nadu during the month of April from 1958-1971. These wages were reported in *Agricultural Wages in India*, published by the Government of India.
2. The letters "D" and "H" signify years in which there was a drought (rain below the 20th percentile of the district's historical rainfall distribution) or very good rainfall (rain above the 80th percentile of the district's historical rainfall distribution), respectively.

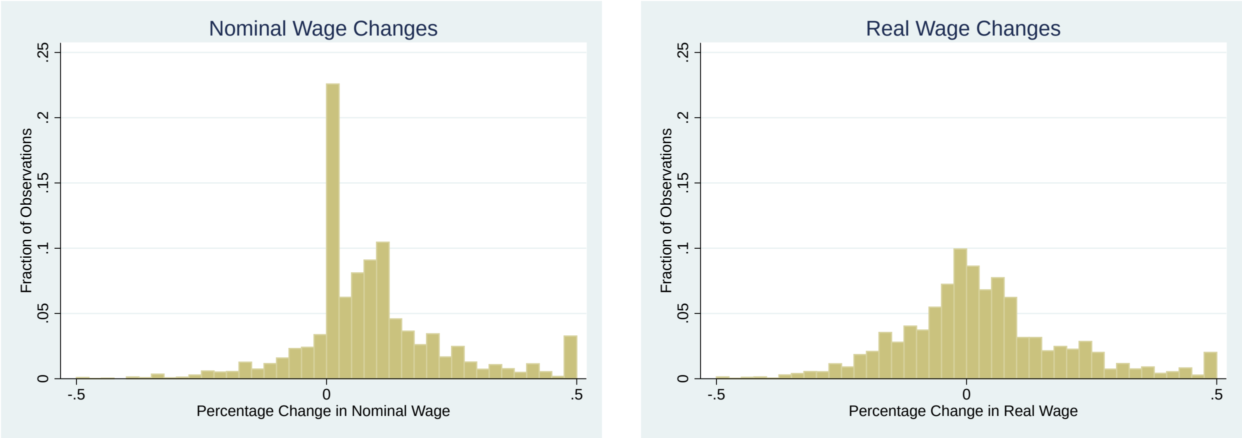


Figure 2 – Distributions of Wage Changes

Notes:

1. The figures plot year-to-year percentage changes in agricultural wages in the World Bank Climate and Agriculture dataset. The unit of observation is a district-year, with data on 256 districts from 1956-1987.
2. Nominal wage changes are shown for the full sample (7,680 observations).
3. Real wages are computed as the nominal wage divided by the state CPI for agricultural workers, for the years in which state CPI data is available (6,850 observations).
4. Wage changes are top coded at 50% and bottom coded at –50%.

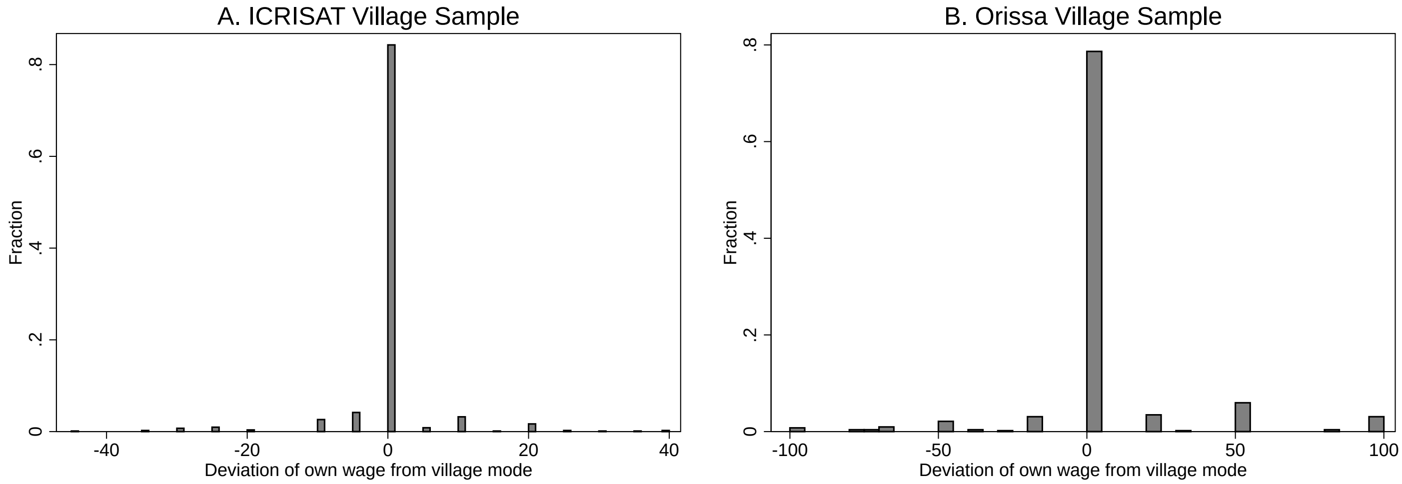


Figure 3 – Dispersion of Agricultural Wages

Notes:

1. Each panel displays the distribution of: (wage reported by worker) – (gender-specific mode of wages in village).
2. Panel A uses observations from the 2001-2004 ICRISAT Village Level Studies. Respondents were asked to report their average daily wage in the past year or season. Sample is restricted to “Daily wage earners” who report their work type as agricultural labor. Observations are at the worker-year level. N=6 villages, 259 households.
3. Panel B uses data collected by Breza, Kaur, and Shamdasani (2017). Respondents were asked to list their work activity and wage level for each of the past 10 days. Observations are at the worker-day level. N=25 villages, 185 male workers.

Table 1
Effect of Rainfall Shocks on Wages
Dependent Variable: Log Nominal Daily Agricultural Wage

	Source: World Bank Data (1956-1987)			Source: National Sample Survey Data (1982-2009)		
	All observations	All observations	Non-positive shock this year	All observations	All observations	Non-positive shock this year
	(1)	(2)	(3)	(4)	(5)	(6)
Positive shock this year	0.021			0.059		
	(0.009)**			(0.018)***		
Negative shock this year	-0.004			0.007		
	(0.010)			(0.023)		
Positive shock last year		0.017	0.026		0.030	0.050
		(0.009)**	(0.010)***		(0.021)	(0.023)**
Negative shock last year		0.007	-0.001		0.005	0.019
		(0.009)	(0.011)		(0.022)	(0.023)
Observations: district-years	7,680	7,680	5,948	--	--	--
Observations: individual-years	--	--	--	59,243	59,243	50,158

Notes:

1. The dependent variable is the log of the nominal daily wage for casual agricultural work.
2. A positive (negative) shock is defined as rainfall in the first month of the monsoon above (below) the 80th (20th) percentile of the district’s usual distribution. No shock is rainfall between the 20th-80th percentile of the district’s usual distribution.
3. Cols (3) and (6) restrict analysis to observations where there was a negative shock or no shock this year.
4. All regressions include district and year fixed effects. Standard errors are clustered by region-year.

Table 2
Test for Wage Adjustment

Dependent Variable: Log Nominal Daily Agricultural Wage

		Source: World Bank (1956-1987)		Source: National Sample Survey (1982-2009)			
		Full sample (1)	Full sample (2)	Full sample (3)	Full sample (4)	Laborers (5)	Full sample (6)
Last year's shock	*This year's shock*						
None, Negative, or Positive	Positive	0.026	0.043	0.063	0.072	0.071	0.066
		(0.009)***	(0.009)***	(0.018)***	(0.019)***	(0.019)***	(0.016)***
None or Negative	Negative	-0.011	-0.014	0.001	0.001	0.000	-0.000
		(0.010)	(0.010)	(0.024)	(0.023)	(0.024)	(0.022)
Positive	Negative	0.035	0.052	0.046	0.058	0.064	0.054
		(0.020)*	(0.021)**	(0.042)	(0.041)	(0.039)*	(0.039)
Positive	None	0.020	0.037	0.058	0.064	0.060	0.064
		(0.010)**	(0.011)***	(0.024)**	(0.024)***	(0.025)**	(0.022)***
Female worker							-0.213
							(0.028)***
Household land size (acres)							0.0000
							(0.0003)
Education							0.0025
							(0.0037)
Prior shock history controls?		No	Yes	No	Yes	Yes	Yes
Observations: district-years		7,680	7,680	--	--	--	--
Observations: individual-years		--	--	59,243	59,243	51,697	52,278
Dependent variable mean		1.21	1.21	3.39	3.39	3.39	3.39

Notes:
1. The dependent variable is the log of the nominal daily wage for casual agricultural work.
2. A positive (negative) shock is defined as rainfall in the first month of the monsoon above (below) the 80th (20th) percentile of the district's usual distribution. No shock ("None") is rainfall between the 20th-80th percentile of the district's usual distribution.
3. The shock sequences are presented as the shock in the previous year and the shock in the current year. Each of the 4 shock covariates are indicators that equal 1 if the sequence of shocks was realized and zero otherwise. The omitted category in each regression is {None or Negative} last year and {None} this year.
4. All regressions include district and year fixed effects. Cols. (2) and (4)-(6) add controls for positive shocks 2 years ago and 3 years ago. Col. (6) includes fixed effects for quarter of the year. Col. (5) limits analysis to individuals whose primary source of earnings is casual daily labor.
5. Standard errors are clustered by region-year.

Table 3
Impact of Inflation on Wage Adjustment
Dependent Variable: Log Nominal Daily Agricultural Wage

			Inflation measure: *Inflation rate*		Inflation measure: *Indicator: Inflation > 6%*	
			(1)	(2)	(3)	(4)
	Last year's shock	This year's shock				
1	Any	Positive	0.027	0.043	0.032	0.047
			(0.009)***	(0.010)***	(0.010)***	(0.011)***
2	*Interaction with inflation measure*		0.002	0.009	-0.016	-0.013
			(0.095)	(0.094)	(0.019)	(0.019)
3	None or Negative	Negative	0.005	0.000	0.006	0.001
			(0.012)	(0.012)	(0.014)	(0.013)
4	*Interaction with inflation measure*		-0.230	-0.184	-0.038	-0.031
			(0.107)**	(0.104)*	(0.021)*	(0.020)
5	Positive	Negative	0.067	0.084	0.069	0.085
			(0.025)***	(0.025)***	(0.028)**	(0.029)***
6	*Interaction with inflation measure*		-0.481	-0.479	-0.083	-0.082
			(0.203)**	(0.205)**	(0.037)**	(0.037)**
7	Positive	None	0.041	0.057	0.042	0.057
			(0.014)***	(0.014)***	(0.015)***	(0.015)***
8	*Interaction with inflation measure*		-0.257	-0.248	-0.047	-0.045
			(0.096)***	(0.097)**	(0.019)**	(0.020)**
Shock history controls			No	Yes	No	Yes
Observations: district-years			7680	7680	7680	7680
R2			0.947	0.948	0.947	0.947
F-test p-value: Coefficient 3 + Coefficient 4 = 0			--	--	0.043**	0.049**
F-test p-value: Coefficient 5 + Coefficient 6 = 0			--	--	0.566	0.891
F-test p-value: Coefficient 7 + Coefficient 8 = 0			--	--	0.690	0.316

Notes:

1. The dependent variable is the log of the nominal wage for casual daily agricultural work. Observations are from the World Bank data.
2. A positive (negative) shock is defined as rainfall in the first month of the monsoon above (below) the 80th (20th) percentile of the district's usual distribution. No shock ("None") is rainfall between the 20th-80th percentile of the district's usual distribution.
3. The shock sequences are presented as the shock in the previous year and the shock in the current year. Each of the 4 shock covariates (rows 1, 3, 5, 7) is an indicator that equals 1 if the sequence of shocks was realized and zero otherwise. The omitted category in each regression is {None or Negative} last year and {None} this year.
4. The remaining covariates (rows 2, 4, 6, 8) are interactions of the shock sequence indicators with a measure of inflation. Inflation is the percentage change in the state CPI for Agricultural Labourers, averaged across all states excluding the district's own state; for 1956 and 1957, the national CPI is used because state CPI data is unavailable. The inflation measure in Cols. (1)-(2) is the continous inflation rate, and in Cols. (3)-(4) is a binary indicator for inflation above 6%.
5. All regressions include district and year fixed effects. Cols. (2) and (4) add controls for positive shocks 2 years ago and 3 years ago. Standard errors are clustered by region-year.

Table 4
Test for Employment Effects

			Dependent variable			
			Total worker-days in agriculture			Non-agri employment
			(1)	(2)	(3)	(4)
	Panel A: Simple specification					
	Positive shock last year		-0.117	-0.153	-0.193	-0.014
			(0.051)**	(0.051)***	(0.059)***	(0.027)
	Positive shock last year x Acres per adult in HH				0.067	0.016
					(0.054)	(0.20)
	Panel B: Full specification					
	Last year's shock	This year's shock				
1	Any	Positive	0.145	0.100	0.074	-0.033
			(0.063)**	(0.068)	(0.080)	(0.027)
2	*Interaction with acres per adult in HH*				0.053	0.030
					(0.068)	(0.026)
3	None or Negative	Negative	-0.094	-0.096	-0.188	0.011
			(0.055)*	(0.055)*	(0.071)***	(0.024)
4	*Interaction with acres per adult in HH*				0.136	-0.020
					(0.069)**	(0.021)
5	Positive	Negative	-0.254	-0.289	-0.416	0.009
			(0.084)***	(0.086)***	(0.090)***	(0.053)
6	*Interaction with acres per adult in HH*				0.212	0.013
					(0.060)***	(0.055)
7	Positive	None	-0.099	-0.130	-0.146	-0.013
			(0.066)	(0.065)**	(0.074)**	(0.035)
8	*Interaction with acres per adult in HH*				0.027	0.011
					(0.063)	(0.032)
	Acres per adult in HH				0.709	-0.386
					(0.118)***	(0.043)***
	(Acres per adult in HH)^2				-0.201	0.085
					(0.034)***	(0.043)***
Previous shock history controls?			No	Yes	Yes	Yes
F-test p-value: Coefficient 3 = Coefficient 5			0.087*	0.045**	0.027**	--
Observations: individual-years			632,327	632,327	632,327	632,327
Dependent variable mean			1.74	1.74	1.74	0.28

Notes:
1. The dependent variable in Cols. (1)-(3) is the number of days in the last 7 days in which the worker did any agricultural work (own farm work plus hired out work). In Col. (4) it is the number of days in the last 7 days in which the worker was hired for any non-agricultural work. Observations are from the NSS data.
2. A positive (negative) shock is defined as rainfall in the first month of the monsoon above (below) the 80th (20th) percentile of the district's usual distribution. No shock ("None") is rainfall between the 20th-80th percentile of the district's usual distribution.
3. In Panel A, the shock covariate is a dummy for a positive shock in the previous year.
4. In Panel B, each of the 4 shock covariates (rows 1, 3, 5, 7) is an indicator that equals 1 if the sequence of shocks (presented as the shock in the previous year and the shock in the current year) was realized and equals 0 otherwise. The omitted category in these regressions is {None or Negative} last year and {None} this year. Each covariate is interacted with number of acres per adult in the household (rows 2, 4, 6, 8).
5. All regressions include district and year fixed effects. Cols. (2) and (4) add controls for positive shocks 2 years ago and 3 years ago. Standard errors are clustered by region-year.

Table 5
Compositional Changes in Labor Allocation

	Dependent Variable	*Total worker-days in agriculture*	*Worker-days as wage laborer*	*Worker-days on own farm*
		(1)	(2)	(3)
1	Positive shock last year	-1.729	-1.198	-0.531
		(0.503)***	(0.438)***	(0.299)*
2	Positive shock last year x Below median landholding	1.734	0.754	0.980
		(0.625)***	(0.520)	(0.306)***
3	Positive shock last year x Above median landholding	1.289	1.351	-0.058
		(0.585)**	(0.545)**	(0.410)
	Below median landholding	-1.017	-2.107	1.092
		(0.308)***	(0.263)***	(0.176)***
	Above median landholding	-0.618	-4.171	3.549
		(0.373)*	(0.358)***	(0.234)***
F-test p-value: Coefficient 1 + Coefficient 2 = 0		0.989	0.046**	0.047**
Observations: household-years		166,003	166,003	166,003
Dependent variable mean: Landless & marginal		5.152	5.016	0.136
Dependent variable mean: Below median land		4.179	2.770	1.410
Dependent variable mean: Above median land		5.022	0.882	4.140

Notes:

1. The table decomposes agricultural employment in the past 7 days. The dependent variable in Col. (2) is the number of worker-days household members worked as hired casual wage laborers for others; in Col. (3) it is the number of worker-days household members worked on their own land; and Col. (1) is the total number of worker-days in agriculture (own farm work plus hired out work). Observations are from the NSS data.
2. A positive shock is defined as rainfall in the first month of the monsoon above the 80th percentile of the district's usual distribution. The sample is comprised of observations in which there is no positive shock this year.
3. The regressions interact the lagged positive shock covariate with binary indicators for landholding categories. The omitted category is landless and marginal landowners--those with less than 0.01 acres per adult in the household. The median landholding is approximately 0.4 acres per adult in the household.
5. All regressions include district and year fixed effects. Standard errors are clustered by region-year.

Table 6: Fairness Norms in Rural Labor Markets

Proportion of respondents saying the scenario is "unfair" or "very unfair"

		All	Laborers	Employers
	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	0.68	0.57
	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	0.59	0.52
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	0.71	0.87
	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	0.71	0.58
	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	0.53	0.23
	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	0.09	0.08
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	0.33	0.24
	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	0.78	0.44
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	0.47	0.59
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	0.70	0.57
8	There are 20 landowners in a village. The prevailing wage during ploughing 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	0.52	0.39

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 Balu's situation, and offers him the job at: A) Rs. 120 B) Rs. 100. Given his need for money, Balu accepts the job. How carefully will he weed?

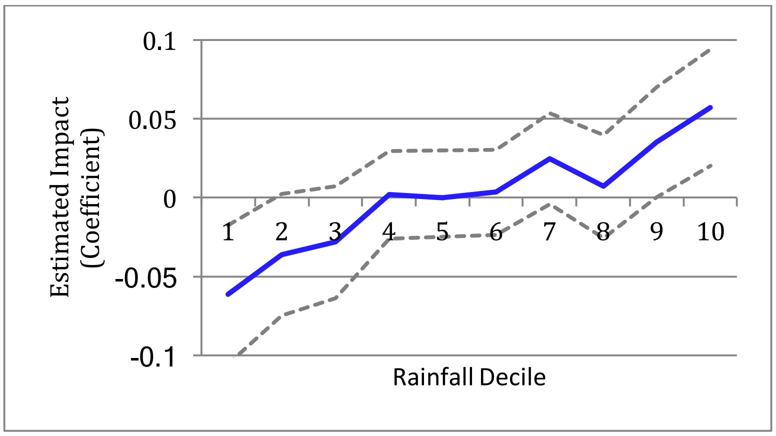
	More carefully than usual	With the normal amount of care	Less carefully than usual
A) Rs. 120	0.55	0.44	0.01
B) Rs. 100	0.06	0.54	0.40

Notes:

1. The sample is comprised of 196 casual laborers and 200 landowning farmers (employers) from 34 villages across 6 districts in the states of Orissa and Madhya Pradesh. Respondents were working males aged 20-80.
2. 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 scenario in each pair. They were asked to rate each scenario as "Very fair", "Fair", "Unfair", or "Very Unfair". The table reports the proportion selecting "Unfair" or "Very Unfair".

ONLINE APPENDICES

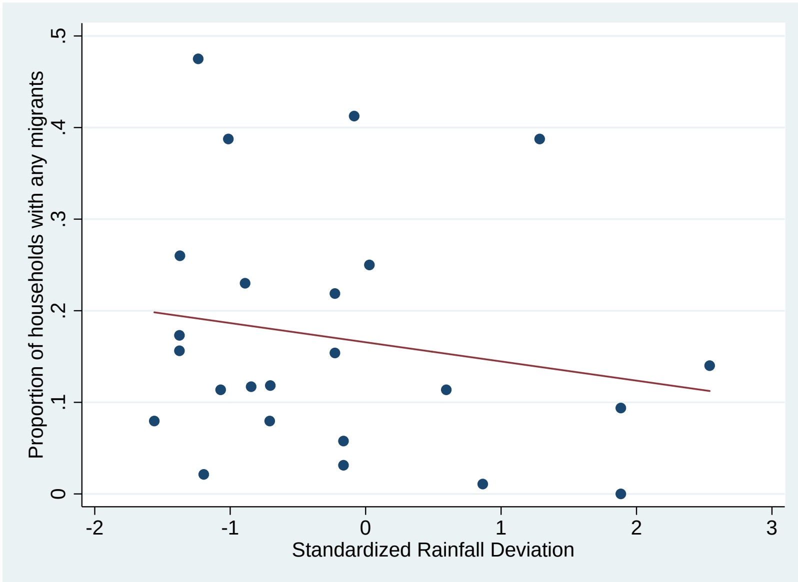
APPENDIX A: APPENDIX TABLES AND FIGURES



Appendix Figure 1 – Impact of Rainfall on Log Crop Yield

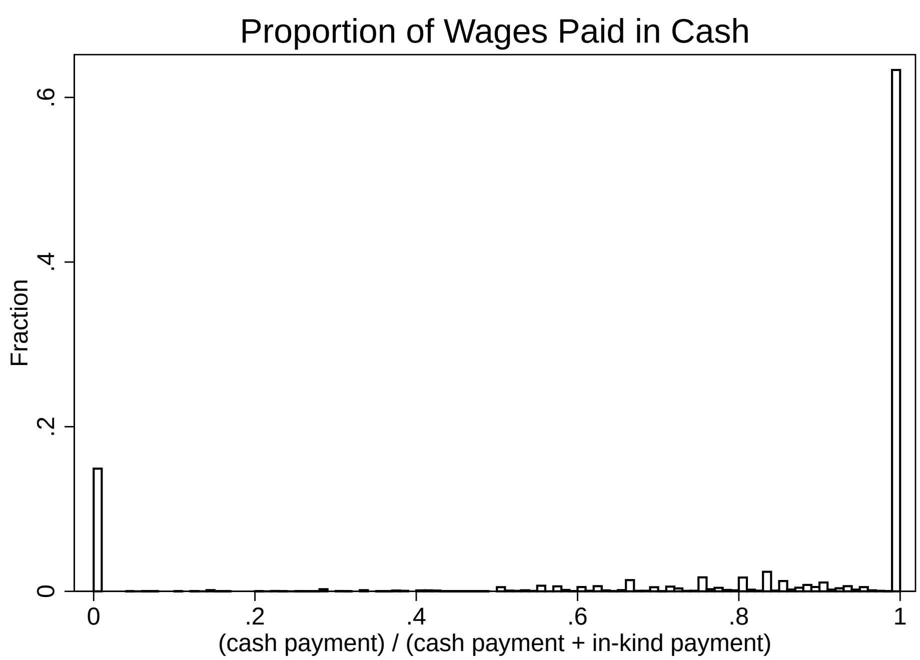
Notes:

1. The figure plots coefficients and 95% confidence intervals from a regression of log crop yields on dummies for each decile of the rainfall distribution.
2. Log crop yields is the log of a weighted average of yields of the 20 crops for which data is available in the World Bank dataset. The yield for each crop has first been normalized by the mean yield of that crop in the district. Weights are the mean percentage of land area planted with a given crop in a district.
3. Each decile dummy equals 1 if rainfall in the first month of the monsoon in the current year fell within the given decile of the district's usual rainfall distribution for that month and equals 0 otherwise. The confidence interval for the 5th decile, which is the omitted category, is computed by averaging the confidence intervals for the 4th and 6th deciles.
4. Each regression contains district and year fixed effects, and controls for lagged positive and lagged negative shocks in the past 5 years. Analysis is limited to districts with non-positive shocks in the previous year to improve precision.
5. Standard errors are corrected to allow for clustering by region-year.



Appendix Figure 2 – Relationship between Rainfall and Migration

Notes:
1. Observations are village-years from the ICRISAT VLS 2001-2004 data.
2. The y-axis measures the proportion of households that reported any out migration in a given village-year.
3. The x-axis is standardized deviation of June rainfall (the month of monsoon arrival for all these villages).



Appendix Figure 3 – Proportion of Wages Paid in Cash

Notes:
1. Histogram plots the proportion of the casual agricultural wage payment that was paid in cash.
2. Observations are from the National Sample Survey data.

Appendix Table 1
Summary Statistics

Variable	Mean	Standard Deviation	Observations: District-years	Observations: Individual-years	Source
Rainfall shocks					
% Positive Shock (1956-1987)	0.226	0.418	7,680	--	Univ of Delaware
% No Shock (1956-1987)	0.626	0.484	7,680	--	Univ of Delaware
% Negative Shock (1956-1987)	0.149	0.356	7,680	--	Univ of Delaware
% Positive Shock (1982-2009)	0.149	0.356	3,548	--	Univ of Delaware
% No Shock (1982-2009)	0.627	0.484	3,548	--	Univ of Delaware
% Negative Shock (1982-2009)	0.224	0.417	3,548	--	Univ of Delaware
Wage and employment variables					
Log nominal agricultural wage (1956-1987)	1.208	0.817	7,680	--	World Bank
Log nominal agricultural wage (1982-2009)	3.390	0.470	--	59,243	Natl Sample Survey
Agricultural employment in past week	1.743	2.783	--	632,327	Natl Sample Survey
Other measures					
Inflation	0.066	0.095	7,680	--	CPI for Agri Labourers
Acres possessed by household	2.750	6.336	--	632,327	Natl Sample Survey
Acres per adult in household	0.633	0.821	--	632,327	Natl Sample Survey

Notes:
1. A positive (negative) shock is defined as rainfall in the first month of the monsoon above (below) the 80th (20th) percentile of the district's usual distribution. No shock is rainfall between the 20th-80th percentile of the district's usual distribution.
2. The nominal agricultural wage is the daily wage for casual agricultural work in each dataset.
3. Agricultural employment is the number of worker-days in the past week the individual was employed in agricultural work (either own farm or on someone else's farm).
4. Inflation equals the percentage change in the state-level CPI for Agricultural Labourers from last year to this year. In the years where state CPI is not available, national CPI is used to compute inflation (the years 1956 and 1957).

Appendix Table 2
Test for Serial Correlation in Rainfall

Dependent variable: Rainfall deviation in the current year

	Sample			
	World Bank data districts (1956 - 1987)		NSS data districts (1982 - 2009)	
	(1)	(2)	(3)	(4)
Rainfall deviation in the previous year	-0.031	-0.058	-0.014	0.054
	(0.034)	(0.032)*	(0.073)	(0.097)
District and year fixed effects?	No	Yes	No	Yes
Observations: district-years	7,680	7,680	3,548	3,548

Notes:
1. This table tests for serial correlation in rainfall. The unit of observation is a district-year.
2. Rainfall deviation is the rainfall level in inches in the first month of the monsoon minus the district's median (50th percentile) rainfall level in that month in the sample distribution. The sample distribution for the World Bank data is computed for the years 1956-1987. The sample distribution for the NSS data is computed for the years 1982-2009.
3. Each column shows results of an OLS regression of the district's rainfall deviation in the current year on the district's rainfall deviation in the previous year. The regressions are run for the district-years of data included each respective dataset: 1956-1987 in the World Bank data and the 9 years covered in the NSS data.
4. Standard errors in each regression are corrected to allow for clustering by geographic region, as defined in the NSS data.

Appendix Table 3
Summary Statistics: Wage Change Premiums

		Mean Relative Wage Change (1)	Standard error (2)
Last year's shock	*This year's shock*		
Any	Positive	0.0388	0.0400
None or Negative	Negative	-0.0127	0.0412
Positive	Negative	0.0138	0.0716
Positive	None	0.0332	0.0440

Notes: This table summarizes wage change patterns for each shock category relative to the reference category in the paper. I compute the wage change as the difference between the log of the current year's wage and the log of the previous year's wage. The above presents the simple mean difference between each shock category and the reference category for this wage change variable. The estimates come from regressing the wage change on the left hand side on dummies for each shock category.

Appendix Table 4

Test for Wage Adjustment: 9-cell Specification

Dependent Variable: Log Nominal Daily Agricultural Wage

			Source: World Bank (1956-1987)			Source: NSS (1982-2009)		
			(1)	(2)	(3)	(4)	(5)	(6)
	Last year's shock	*This year's shock*	% Obs			% Obs		
1	None	None	40%	Omitted	Omitted	39%	Omitted	Omitted
2	Negative	None	8%	0.001 (0.011)	-0.002 (0.011)	12%	0.021 (0.022)	0.020 (0.022)
3	None	Positive	14%	0.021 (0.010)**	0.044 (0.011)***	9%	0.086 (0.019)***	0.086 (0.021)***
4	Negative	Positive	3%	0.062 (0.020)***	0.087 (0.020)***	3%	0.093 (0.041)**	0.088 (0.042)**
5	Positive	Positive	5%	0.015 (0.016)	0.036 (0.016)**	3%	-0.040 (0.034)	-0.041 (0.035)
6	None	Negative	8%	-0.009 (0.012)	-0.011 (0.012)	11%	0.028 (0.023)	0.024 (0.023)
7	Negative	Negative	3%	-0.017 (0.017)	-0.019 (0.017)	3%	-0.060 (0.051)	-0.059 (0.053)
8	Positive	Negative	4%	0.035 (0.020)*	0.059 (0.021)***	8%	0.058 (0.040)	0.061 (0.039)
9	Positive	None	14%	0.020 (0.010)**	0.044 (0.011)***	13%	0.065 (0.023)***	0.064 (0.024)***
	Prior shock history controls?		--	No	Yes	--	No	Yes
	Observations: district-years		7,680	7,680	7,680	3,548	--	--
	Observations: individual-years		--	--	--	--	59,243	59,243

Notes:

1. The dependent variable is the log of the nominal wage for casual daily agricultural work.
2. A positive (negative) shock is defined as rainfall in the first month of the monsoon above (below) the 80th (20th) percentile of the district's usual distribution. No shock ("None") is rainfall between the 20th-80th percentile of the district's usual distribution.
3. The shock sequences are presented as the shock in the previous year and the shock in the current year. Each of the 8 shock covariates is an indicator that equals 1 if the sequence of shocks was realized and equals zero otherwise. The omitted category in each regression is {None} last year and {None} this year. Cols. (1) and (4) indicate the percentage of observations in which each shock sequence was realized.
4. All regressions include district and year fixed effects. Cols. (3) and (6) add controls for positive shocks 2 years ago and 3 years ago. Standard errors are clustered by region-year.

Appendix Table 5

Effects by Gender

Dependent Variable: Log Nominal Daily Agricultural Wage

		Males	Females
		(1)	(2)
Last year's shock	*This year's shock*		
Any	Positive	0.0860***	0.0515***
		(0.023)	(0.017)
None or Negative	Negative	-0.000143	-0.0132
		(0.024)	(0.022)
Positive	Negative	0.0844*	0.0179
		(0.047)	(0.036)
Positive	None	0.0872***	0.0426**
		(0.032)	(0.021)
Observations: individual-years		30,201	29,007
R2		0.599	0.570

Notes:
1. This table replicates the main specification separately for male and female laborers.
2. Observations are from the NSS data. Note that the gender variable is missing for 35 observations, which are therefore excluded in this table.
3. All regressions include district and year fixed effects, as well as controls for positive shocks 2 years ago and 3 years ago.
4. Standard errors are clustered by region-year.

Appendix Table 6

Effects for Cash vs. In-Kind Wage Payments

		Dependent variable: Cash wage payment		Dependent variable: In-kind wage payment		
		Log wage	Wage level	Log wage	Wage level	Proportion
		(1)	(2)	(3)	(4)	(5)
Last year's shock	*This year's shock*					
Any	Positive	0.0718***	3.144***	-0.0761	-0.586	-0.0185
		(0.020)	(0.819)	(0.078)	(0.379)	(0.014)
None or Negative	Negative	-0.0324	-0.609	0.0699	0.612*	0.000516
		(0.025)	(0.924)	(0.077)	(0.351)	(0.010)
Positive	Negative	0.0745	3.853**	-0.149	-1.669**	-0.0711***
		(0.050)	(1.812)	(0.100)	(0.760)	(0.026)
Positive	None	0.0459**	2.821**	-0.109	-0.548	-0.0283**
		(0.021)	(1.422)	(0.088)	(0.764)	(0.013)
Observations: individual-years		48,892	55,825	19,529	55,825	55,825
R2		0.530	0.520	0.618	0.453	0.531
Dependent variable mean		3.297	25.88	2.482	6.167	0.202

Notes:
1. This table replicates the main specification separately for the cash and (monetary value of) the in-kind components of the daily wage payment.
2. The dependent variable in Cols. (1) and (3) is the log of the payment amount. In Cols. (2) and (4) it is the payment level (included for robustness due to the presence of zero cash or in-kind payment levels for some observations). In Col. (5) it is the proportion of the in-kind wage payment: in-kind / total payment.
3. Shocks are defined exactly as in the main specification in the paper. The omitted shock category in each regression is {None or Negative} last year and {None} this year.
4. All regressions include district and year fixed effects, as well as controls for positive shocks 2 years ago and 3 years ago.
5. Standard errors are clustered by region-year.
6. Observations are from NSS data. In round 55 of the survey, information on the cash versus in-kind components of the payment were not separately recorded for some observations; these are omitted from the analysis.

Appendix Table 7
Wage Adjustment for Flat Rate vs. Piece Rate Contracts
Dependent Variable: Log Nominal Daily Cash Payment

	Last year's shock	This year's shock	Rounds with contract type (1)	Rounds with contract type (2)	All rounds (3)
1	Any	Positive	0.0923**	0.102**	0.120***
			(0.041)	(0.045)	(0.038)
2	*Interaction with piece rate dummy*		-0.0153	-0.0159	-0.00809
			(0.072)	(0.072)	(0.068)
3	None or Negative	Negative	0.0306	0.0273	0.0172
			(0.040)	(0.041)	(0.041)
4	*Interaction with piece rate dummy*		-0.0772	-0.0754	-0.0923
			(0.092)	(0.092)	(0.086)
5	Positive	Negative	0.0335	0.0690	0.0375
			(0.063)	(0.062)	(0.057)
6	*Interaction with piece rate dummy*		-0.00259	-0.00494	-0.0000641
			(0.061)	(0.061)	(0.057)
7	Positive	None	0.111*	0.131**	0.139**
			(0.065)	(0.066)	(0.054)
8	*Interaction with piece rate dummy*		-0.117	-0.119	-0.114
			(0.106)	(0.105)	(0.098)
9	Piece rate dummy		0.00634	0.00666	0.00693
			(0.030)	(0.030)	(0.028)
	Shock history controls		No	Yes	Yes
	Observations: district-years		15864	15864	48512

Notes:
1. The dependent variable is the log nominal cash payment for a day of casual agricultural work.
2. Shocks are defined as in the main specifications in the paper.
3. The remaining covariates (rows 2, 4, 6, 8) are interactions of each respective shock sequence indicator with a dummy that equals 1 if the worker was paid a piece rate and equals 0 for a flat wage.
4. In the NSS, contract terms (whether the payment was a flat wage, piece rate, etc.) are only provided in rounds 55, 61, and 66. Cols. (1)-(2) are restricted to observations in which contract terms are defined. To increase power by improving the estimation of the fixed effects, Col. (3) includes observations from all rounds, and adds a full set of interactions of all covariates with a dummy for rounds in which contract terms are not defined; consequently, the displayed coefficients provide the effects for only the rounds of interest (55, 61, 66).
5. All regressions include district and year fixed effects. Cols. (2)-(3) add controls for positive shocks 2 years ago and 3 years ago. Standard errors are clustered by region-year.

Appendix Table 8
Robustness to Definition of Rainfall Shocks: NSS Data Results

		Percentile Cut-off for Positive/Negative Shocks				
		80/20	80/25	80/30	75/25	70/30
		(1)	(2)	(3)	(4)	(5)
Last year's shock	*This year's shock*					
Panel A - Dependent Variable: Log Nominal Daily Wage						
Any	Positive	0.072	0.075	0.075	0.067	0.056
		(0.019)***	(0.020)***	(0.019)***	(0.019)***	(0.021)***
None or Negative	Negative	0.001	0.013	0.013	0.021	0.025
		(0.023)	(0.021)	(0.020)	(0.023)	(0.024)
Positive	Negative	0.058	0.087	0.090	0.063	0.047
		(0.041)	(0.038)**	(0.036)**	(0.037)*	(0.033)
Positive	None	0.064	0.042	0.037	0.054	0.018
		(0.024)***	(0.024)*	(0.022)	(0.022)**	(0.023)
Panel B - Dependent Variable: Agricultural Employment						
Any	Positive	0.100	0.093	0.082	0.080	-0.020
		(0.068)	(0.070)	(0.071)	(0.066)	(0.071)
None or Negative	Negative	-0.096	-0.089	-0.112	-0.081	-0.111
		(0.055)*	(0.053)*	(0.056)**	(0.054)	(0.063)*
Positive	Negative	-0.289	-0.283	-0.308	-0.233	-0.288
		(0.086)***	(0.077)***	(0.077)***	(0.073)***	(0.079)***
Positive	None	-0.130	-0.114	-0.094	-0.047	-0.094
		(0.065)**	(0.073)	(0.075)	(0.077)	(0.074)

Notes:
1. This tables examines robustness of the results to alternate cut-offs for positive and negative shocks in the NSS data. The dependent variable in Panel A is the log of the nominal wage for casual daily agricultural work, and in Panel B is total number of days worked in agriculture (on one's own farm or as a hired laborer on someone else's farm).
2. In each column, positive and negative shocks are defined under different cut-offs, as labeled at the top of each column. E.g., in Col (1), a positive (negative) shock is defined as rainfall in the first month of the monsoon above (below) the 80th (20th) percentile of the district’s usual distribution. This corresponds to the definiton of shocks in the main specification in the paper. Similarly, in Col. (2), a positive (negative) shock is defined as rainfall in the first month of the monsoon above (below) the 80th (25th) percentile of the district’s usual distribution, and so on.
3. All regressions include district and year fixed effects and controls for positive shocks 2 years ago and 3 years ago.
4. Standard errors are clustered by region-year.

Appendix Table 9
Robustness to Definition of Rainfall Shocks: World Bank Data Results

		Percentile Cut-off for Positive/Negative Shocks				
		80/20	80/25	80/30	75/25	70/30
		(1)	(2)	(3)	(4)	(5)
Last year's shock	*This year's shock*					
Any	Positive	0.0474***	0.0418***	0.0410***	0.0445***	0.0444***
		(0.013)	(0.010)	(0.010)	(0.010)	(0.011)
Interaction with 1{Inflation> 6%}		-0.013	-0.00735	-0.00699	-0.00832	-0.0121
		(0.018)	(0.018)	(0.018)	(0.017)	(0.016)
None or Negative	Negative	0.000586	-0.0123	-0.0139	-0.0137	-0.0188
		(0.013)	(0.012)	(0.012)	(0.013)	(0.013)
Interaction with 1{Inflation> 6%}		-0.0312	-0.0190	-0.0142	-0.0195	-0.0154
		(0.020)	(0.018)	(0.017)	(0.018)	(0.017)
Positive	Negative	0.0849***	0.0738***	0.0720***	0.0743***	0.0711***
		(0.029)	(0.026)	(0.024)	(0.024)	(0.021)
Interaction with 1{Inflation> 6%}		-0.0816**	-0.0714**	-0.0572*	-0.0678**	-0.0594**
		(0.037)	(0.032)	(0.030)	(0.031)	(0.028)
Positive	None	0.0573***	0.0519***	0.0504***	0.0510***	0.0451***
		(0.015)	(0.016)	(0.017)	(0.016)	(0.015)
Interaction with 1{Inflation> 6%}		-0.0445**	-0.0397*	-0.0432**	-0.0422**	-0.0489**
		(0.020)	(0.020)	(0.021)	(0.020)	(0.020)
F-test p-value: Coeff 3 + Coeff 4 = 0		0.0486	0.0152	0.0184	0.00874	0.00383
F-test p-value: Coeff 5 + Coeff 6 = 0		0.891	0.902	0.434	0.759	0.555
F-test p-value: Coeff 7 + Coeff 8 = 0		0.316	0.356	0.584	0.506	0.780

Notes:
1. This tables examines robustness of the results to alternate cut-offs for positive and negative shocks in the World Bank data. It replicates the regression in Col. (4) of Table 3 under different shock definitions.
2. In each column, positive and negative shocks are defined under different cut-offs, as labeled at the top of each column. E.g., in Col (1), a positive (negative) shock is defined as rainfall in the first month of the monsoon above (below) the 80th (20th) percentile of the district’s usual distribution. This corresponds to the definiton of shocks in the main specification in the paper. Similarly, in Col. (2), a positive (negative) shock is defined as rainfall in the first month of the monsoon above (below) the 80th (25th) percentile of the district’s usual distribution, and so on.
3. All regressions include district and year fixed effects and controls for positive shocks 2 years ago and 3 years ago.
4. Standard errors are clustered by region-year.

Appendix Table 10
Correlation of Shocks with Prices and Inflation

		Dependent variable				
		Own CPI	Own harvest price	Other states' CPI	Other states' harvest price	Other states' inflation
		(1)	(2)	(3)	(4)	(5)
Last year's shock	*This year's shock*					
None, Drought, or Positive	Positive	0.67	-0.42	-0.24	0.13	0.0001
		(1.24)	(2.29)	(0.17)	(0.35)	(0.0006)
None or Drought	Drought	-1.17	0.79	0.13	-0.20	0.0009
		(1.84)	(2.43)	(0.24)	(0.33)	(0.0012)
Positive	Drought	-5.54	-2.27	0.42	0.79	0.0028
		(3.45)	(4.75)	(0.46)	(0.56)	(0.0014)*
Positive	None	-1.77	-1.08	-0.02	0.21	0.0017
		(2.17)	(2.83)	(0.30)	(0.40)	(0.0012)
Observations: district-years		6,851	7,680	7,440	7,680	7,680
Dependent variable mean		275	111	260	117	0.066

Notes:

1. Own CPI is the district's state-level CPI for Agricultural Labourers. Own harvest price is the harvest price for paddy (i.e. rice) (given in the World Bank dataset). Inflation is the percentage change in the CPI for Agricultural Labourers since the previous year. The dependent variables in Cols. (3)-(6) are computed by averaging values for all states except the district's own state.
2. A positive (negative) shock is defined as rainfall in the first month of the monsoon above (below) the 80th (20th) percentile of the district’s usual distribution. No shock ("None") is rainfall between the 20th-80th percentile of the district’s usual distribution.
3. The shock sequences are presented as the shock in the previous year and the shock in the current year. Each of the 4 shock covariates is an indicator that equals 1 if the sequence of shocks was realized and equals zero otherwise. The omitted category in each regression is {None or Negative} last year and {None} this year.
4. All regressions include district and year fixed effects.
5. Standard errors are clustered by region-year.

Appendix Table 11

Inflation Results: Robustness and Placebo Checks

Dependent variable: Log nominal daily agricultural wage

			Interaction Term in Regressions		
			Other states' inflation	*Linear year trend*	*Post-1970 dummy*
			(1)	(2)	(3)
	Last year's shock	This year's shock			
1	None, Drought, or Positive	Positive	0.030	0.026	0.031
			(0.009)***	(0.009)***	(0.013)**
2	*Interaction*		0.005	-0.000	-0.009
			(0.012)	(0.000)	(0.017)
3	None or Drought	Drought	0.005	-0.012	-0.004
			(0.012)	(0.011)	(0.014)
4	*Interaction*		-0.220	-0.001	-0.016
			(0.109)**	(0.001)	(0.022)
5	Positive	Drought	0.077	0.035	0.033
			(0.025)***	(0.020)*	(0.030)
6	*Interaction*		-0.522	-0.001	0.003
			(0.199)***	(0.003)	(0.040)
7	Positive	None	0.045	0.020	0.021
			(0.014)***	(0.010)**	(0.013)
8	*Interaction*		-0.271	0.000	-0.003
			(0.096)***	(0.001)	(0.019)
Observations: district-years			7,200	7,680	7,680
R2			0.946	0.947	0.947
Dependent variable mean			1.27	1.21	1.21

Notes:

1. The dependent variable is the log of the nominal wage for casual daily agricultural work. Observations are from the World Bank data.
2. A positive (negative) shock is defined as rainfall in the first month of the monsoon above (below) the 80th (20th) percentile of the district's usual distribution. No shock ("None") is rainfall between the 20th-80th percentile of the district's usual distribution. The shock sequences are presented as the shock in the previous year and the shock in the current year. Each of the 4 shock covariates (rows 1, 3, 5, 7) is an indicator that equals 1 if the sequence of shocks was realized and zero otherwise. The omitted category in each regression is {None or Negative} last year and {None} this year.
3. The remaining covariates (rows 2, 4, 6, 8) are interactions with the shock sequence indicators. In Col. (1) the interaction term is inflation, which equals the percentage change in the state CPI for Agricultural Labourers, averaged across all states excluding the district's own state; this is not available for 1956 and 1957. In Col. (2) the interaction term is the calendar year of the observation. In Col. (3), it is a binary indicator for whether the year is after 1970.
4. Regressions include district and year fixed effects. Standard errors are clustered by region-year.

Appendix Table 12
Inflation Results: Alternate Inflation Definitions

Dependent variable: Log nominal daily agricultural wage

			Interaction Term in Regressions			
			Current year's inflation	*Avg of current and next year's inflation*	*Avg of current and previous year's inflation*	*Current year's inflation*
			(1)	(2)	(3)	(4)
	Last year's shock	*This year's shock*				
1	None, Drought, or Positive	Positive	0.0474***	0.0529***	0.0594***	0.0440***
			(0.011)	(0.011)	(0.012)	(0.010)
2	*Interaction*		-0.0128	-0.0305	-0.0442*	-0.0108
			(0.019)	(0.022)	(0.023)	(0.019)
3	None or Drought	Drought	-0.000959	-0.00247	-0.0184	-0.000959
			(0.013)	(0.015)	(0.016)	(0.013)
4	*Interaction*		-0.0348	-0.0226	0.00759	-0.0348
			(0.023)	(0.028)	(0.025)	(0.023)
5	Positive	Drought	0.0847***	0.0590	0.0987***	0.0847***
			(0.029)	(0.039)	(0.031)	(0.029)
6	*Interaction*		-0.0758**	-0.0187	-0.121***	-0.0758**
			(0.038)	(0.062)	(0.045)	(0.038)
7	Positive	None	0.0553***	0.0534***	0.0464***	0.0553***
			(0.016)	(0.016)	(0.015)	(0.016)
8	*Interaction*		-0.0334	-0.0457*	-0.0219	-0.0334
			(0.021)	(0.025)	(0.022)	(0.021)
Sample			All	All	All	Exclude 1968 & 1975
Observations: district-years			7,680	7,680	7,680	7,200

Notes:
1. Observations are from the World Bank data.
2. In Cols. (1) and (4), the interaction term is a dummy for inflation>6% in the current calendar year -- Col (1) corresponds to the main specification in the paper. Cols. (2) and (3) average the value of this variable for the current year with the next calendar year (Col. 2) and with the previous calendar year (Col. 3). The robustness checks are similar if the continuous version of variables is used instead.
3. Col (4) drops observations from years 1968 and 1975.
4. Regressions include district and year fixed effects, and controls for positive shocks 2 years ago and 3 years ago. Standard errors are clustered by region-year.

Appendix Table 13
Robustness: Wage Rigidity in Low Inflation Years
Dependent Variable: Log Nominal Daily Agricultural Wage

		Sample		
		Inflation < 4%	Inflation < 2%	Inflation < 1%
		(1)	(2)	(3)
Last year's shock	*This year's shock*			
Any	Positive	0.0438***	0.0361***	0.0363**
		(0.012)	(0.013)	(0.014)
None or Negative	Negative	-0.00388	0.00727	0.00323
		(0.014)	(0.016)	(0.016)
Positive	Negative	0.0628**	0.0530*	0.0527**
		(0.025)	(0.027)	(0.025)
Positive	None	0.0433**	0.0358**	0.0230
		(0.018)	(0.017)	(0.019)
Observations: district-years		2,792	2,312	1,926

Notes:
1. The dependent variable is the log of the nominal wage for casual daily agricultural work.
2. Each of the three columns limits observations to those in which the state inflation rate was less than 4%, 2%, or 1%, respectively, in that calendar year.
3. All regressions include district and year fixed effects and lagged positive shock controls.
4. Standard errors are clustered by region-year.

Appendix Table 14
Effects of Rainfall on Composition & Size of Agricultural Labor Force

		Dependent variable		
		Individual reports being in agricultural labor force	Individual migrated into village	Household member migrated out of village
		(1)	(2)	(3)
Panel A: Simple specification				
Positive shock last year		-0.0034	0.0018	-0.0037
		(0.0039)	(0.0021)	(0.0026)
Panel B: Full specification				
Last year's shock	This year's shock			
Any	Positive	0.0027	-0.0047	-0.0026
		(0.0047)	(0.0017)***	(0.0042)
None or Negative	Negative	0.0025	0.0027	-0.0053
		(0.0035)	(0.0029)	(0.0132)
Positive	Negative	-0.0008	-0.0006	-0.0061
		(0.0070)	(0.0045)	(0.0128)
Positive	None	-0.0048	0.0020	-0.0047
		(0.0045)	(0.0019)	(0.0031)
Observations: individual-years		1,530,688	414,232	
Observations: household-years				36,251
Dependent variable mean		0.389	0.230	0.035

Notes:
1. In Col. (1), the dependent variable is an indicator that equals 1 if the respondent indicated agriculture as his/her primary or subsidiary occupation, and equals 0 otherwise. The sample is comprised of all rural residents from all rounds of the NSS.
2. In Col. (2), the dependent variable is an indicator that equals 1 if the individual is a migrant into the village and 0 otherwise. The sample is comprised of all rural residents in rounds for which questions on individual-level in-migration status were asked (rounds 38, 43, 55).
3. In Col. (3), the dependent variable is an indicator that equals 1 if the household reports having a member who has migrated out in the past year and 0 otherwise. The sample is comprised of all rural households in round 64, which has data on out-migration status by year, surveyed in the final quarter of the agricultural year (so that the 1 year recall links cleanly to agricultural year).
4. A positive (negative) shock is defined as rainfall in the first month of the monsoon above (below) the 80th (20th) percentile of the district’s usual distribution. No shock ("None") is rainfall between the 20th-80th percentile of the district’s usual distribution.
5. In Panel A, the shock covariate is a dummy for a positive shock in the previous year.
6. In Panel B, each of the 4 shock covariates is an indicator that equals 1 if the sequence of shocks (presented as the shock in the previous year and the shock in the current year) was realized and equals zero otherwise. The omitted category in these regressions is {None or Negative} last year and {None} this year.
7. Results are from OLS regressions. Regressions (1) and (2) contain district and year fixed effects. Standard errors are clustered by region-year.

Appendix Table 15
Relationship between Rainfall and Migration (ICRISAT)

Dependent variable	*Any migration* (1)	*Any migration* (2)	*Number of migrants* (3)	*Number of migrants* (4)
Panel A: Continuous rainfall deviation				
Standardized June rain	-0.0260***	-0.0286***	-0.0343**	-0.0410***
	(0.006)	(0.006)	(0.011)	(0.010)
Panel B: Continuous rainfall deviation - Asymmetric effects				
Standardized June rain x Positive deviation	-0.0413***	-0.0437***	-0.0627***	-0.0650**
	(0.008)	(0.010)	(0.016)	(0.018)
Standardized June rain x Negative deviation	-0.00446	-0.00719	0.00562	-0.00701
	(0.016)	(0.018)	(0.025)	(0.030)
Panel C: Binary shocks				
Positive shock (above 80th percentile)	-0.0761***	-0.0841***	-0.0961**	-0.114**
	(0.020)	(0.021)	(0.043)	(0.042)
Negative shock (below 20th percentile)	0.0135	0.0161	0.0197	0.0322
	(0.017)	(0.020)	(0.027)	(0.030)
Village fixed effects?	Yes	No	Yes	No
Household fixed effects?	No	Yes	No	Yes
Observations: household-years	1781	1781	1781	1781
Dependent variable mean	0.177	0.177	0.322	0.322

Notes:
1. Observations are household-years from the ICRISAT VLS 2001-2004 data.
2. The dependent variable in Cols. (1)-(2) is a dummy for whether there was any out migration from the household. In Cols. (3)-(4), the dependent variable is the continuous number of individuals who migrated out of the household at some point during the year.
3. Standardized June rain is the standardized deviation from the mean of June rainfall, where the mean and standard deviation are taken from the rainfall timeseries for that district in the University of Delaware data (same rainfall data as in the main paper).
2. In Panel C, positive and negative shocks are defined exactly as in the main analysis for the NSS data in the paper.
A positive (negative) shock is defined as rainfall in the first month of the monsoon above (below) the 80th (20th) percentile of the district’s usual distribution. No shock ("None") is rainfall between the 20th-80th percentile of the district’s usual distribution. Note that June corresponds to the first month of the monsoon for the ICRISAT villages.
7. Results are from OLS regressions. Regressions (1) and (3) contain village fixed effects, and Cols. (2) and (4) contain household fixed effects. Standard errors are clustered by village-year.

Appendix Table 16
Effects of Rainfall Shocks on Migration (ICRISAT)

		Full sample				Landless & Small farms
		Any migration	Any migration	Number of migrants	Number of migrants	Any migration
		(1)	(2)	(3)	(4)	(5)
Panel A: Simple specification						
Positive shock last year		-0.0208	-0.0255	-0.0518	-0.0794	-0.0180
		(0.033)	(0.040)	(0.049)	(0.053)	(0.029)
Panel B: Full specification						
Last year's shock	*This year's shock*					
Any	Positive	-0.0654**	-0.0731**	-0.0976**	-0.121**	-0.0618**
		(0.024)	(0.025)	(0.047)	(0.043)	(0.026)
None or Negative	Negative	0.0212	0.0237	0.0186	0.0273	0.0230
		(0.020)	(0.023)	(0.030)	(0.034)	(0.026)
Positive	Negative	--	--	--	--	--
Positive	None	0.0354	0.0362	-0.00507	-0.0233	0.0284
		(0.032)	(0.035)	(0.049)	(0.058)	(0.030)
Village fixed effects?		Yes	No	Yes	No	Yes
Household fixed effects?		No	Yes	No	Yes	No
Observations: household-years		1781	1781	1781	1781	1174
Dependent variable mean		0.177	0.177	0.322	0.322	0.175

Notes:
1. Observations are household-years from the ICRISAT VLS 2001-2004 data.
2. The dependent variable in Cols. (1), (2), and (5) is a dummy for whether there was any out migration from the household. In Cols. (3)-(4), the dependent variable is the continuous number of individuals who migrated out of the household at some point during the year.
3. A positive (negative) shock is defined as rainfall in the first month of the monsoon above (below) the 80th (20th) percentile of the district’s usual distribution. No shock ("None") is rainfall between the 20th-80th percentile of the district’s usual distribution.
4. In Panel A, the shock covariate is a dummy for a positive shock in the previous year.
5. In Panel B, each of the 4 shock covariates is an indicator that equals 1 if the sequence of shocks (presented as the shock in the previous year and the shock in the current year) was realized and equals zero otherwise.
6. Results are from OLS regressions. Cols. (1), (3), and (5) contain village fixed effects, and Cols. (2) and (4) contain household fixed effects. Standard errors are clustered by village-year.

Appendix Table 17
Effects of Rain Shocks on Employment over Time
Dependent variable: Total worker-days in agriculture

			Interaction term (Time measure)	
			Year (linear)	Post 1995 dummy
			(1)	(2)
	Panel A: Simple specification			
	Positive shock last year		-0.236**	-0.143**
			(0.117)	(0.071)
	Positive shock last year x Time measure		0.00591	0.0475
			(0.006)	(0.101)
	Panel B: Full specification			
	Last year's shock	This year's shock		
1	Any	Positive	0.207	0.105
			(0.159)	(0.078)
2	Interaction with time measure		-0.00318	0.0819
			(0.008)	(0.133)
3	None or Negative	Negative	-0.0708	-0.0887
			(0.111)	(0.067)
4	Interaction with time measure		-0.00112	-0.0165
			(0.006)	(0.117)
5	Positive	Negative	-0.170	-0.317***
			(0.167)	(0.103)
6	Interaction with time measure		-0.00372	0.0914
			(0.009)	(0.155)
7	Positive	None	-0.242*	-0.124
			(0.143)	(0.084)
8	Interaction with time measure		0.00731	0.0492
			(0.008)	(0.124)
F-test p-value: Coefficient 3 = Coefficient 5			0.087*	0.045**
Observations: individual-years			632,327	632,327
Dependent variable mean			1.74	1.74

Notes:
1. Observations are from the NSS data.
2. In Panel A, the shock covariate is a dummy for a positive shock in the previous year.
3. In Panel B, each of the 4 shock covariates (rows 1, 3, 5, 7) is an indicator that equals 1 if the sequence of shocks was realized and equals zero otherwise.
4. In Panel B, rows 2, 4, 6, and 8 show the coefficients from an interaction of each shock with a time measure. In Col (1), the time measure is a continuous linear variable for the year. This variable has been rescaled so that first year in sample (1982) has a value of 1; i.e. the variable is defined as: (year - 1981). In Col (2), the time measure is a dummy for whether the year is after 1995 (the midpoint of the NSS sample).
5. All regressions include district and year fixed effects. Standard errors clustered by region-year.

Appendix Table 18

Correlation of Shocks with Characteristics of Wage Workers

		Dependent Variable			
		1{Female worker} (1)	Education category (2)	Age (3)	Landholding (4)
Last year's shock	*This year's shock*				
None, Negative, or Positive	Positive	-0.000609	0.0987	0.196	-0.128
		(0.017)	(0.069)	(0.334)	(0.080)
None or Negative	Negative	-0.000678	0.0481	-0.257	-0.278
		(0.014)	(0.045)	(0.381)	(0.222)
Positive	Negative	-0.0171	0.0936	0.0496	0.0701
		(0.022)	(0.075)	(0.570)	(0.121)
Positive	None	-0.00177	-0.0538	-0.719*	0.153
		(0.017)	(0.057)	(0.420)	(0.104)
Prior shock history controls?					
Observations: individual-years		59208	42016	59243	59243
Dependent variable mean		1.48	1.59	33.87	0.81

Notes:

1. The sample is restricted to observations in which a worker did agricultural work for a paid wage (NSS data).
2. Shocks are defined as in the main tables.
3. All regressions include district and year fixed effects, and controls for positive shocks 2 years ago and 3 years ago.
4. Standard errors are clustered by region-year.

Appendix Table 19
Impact of Shocks on Capital Inputs

		Dependent variable		
		Bullocks	Tractors	Fertilizer
		(1)	(2)	(3)
Panel A: Simple specification				
Positive shock last year		-0.001	0.009	-0.004
		(0.010)	(0.024)	(0.022)
Panel B: Full specification				
Last year's shock	*This year's shock*			
None, Drought, or Positive	Positive	0.006	-0.012	-0.023
		(0.011)	(0.026)	(0.024)
None or Drought	Drought	-0.012	-0.011	-0.044
		(0.013)	(0.039)	(0.036)
Positive	Drought	-0.012	-0.037	-0.037
		(0.021)	(0.053)	(0.045)
Positive	None	0.009	0.007	0.005
		(0.011)	(0.030)	(0.028)
Observations: district-years		7,680	7,680	7,680
Dependent variable mean		0.000	0.000	0.000

1. The dependent variables are number of bullocks, number of tractors, and amount of nitrogen fertilizer (the most common fertilizer input) used in rural production. The source is the World Bank dataset. All dependent variables are standardized to have a mean of 0 and standard deviation of 1.
2. A positive (negative) shock is defined as rainfall in the first month of the monsoon above (below) the 80th (20th) percentile of the district's usual distribution. No shock ("None") is rainfall between the 20th-80th percentile of the district's usual distribution.
3. In Panel A, the shock covariate is a dummy for a positive shock in the previous year.
4. In Panel B, each of the 4 shock covariates (rows 1, 3, 5, 7) is an indicator that equals 1 if the sequence of shocks (presented as the shock in the previous year and the shock in the current year) was realized and equals zero otherwise. The omitted category in these regressions is {None or Negative} last year and {None} this year. Each covariate is interacted with the number of acres per adult in the household (rows 2, 4, 6, 8).
5. All regressions include district and year fixed effects.
6. Standard errors are clustered by region-year.

Appendix Table 20
Survey Responses to Employment Scenarios

		Proportion of Responses		
		Yes	Maybe	No
	Panel A: Laborers (N=196)			
1	Do you remember any year when the agricultural wage in this village was less than the wage [for that season] in the year before?	0.00	--	1.00
2a	Have there been times when you would have liked to work at the prevailing wage but did not obtain work?	0.74	--	0.26
2b	How often have you faced this problem of involuntary unemployment? Every year (0.60); Some years (0.12); Rarely (0.02); Never (0.26)	--	--	--
3	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?	0.61	0.20	0.19
4	When you have difficulty finding work at the prevailing wage, do you offer to work at a lower wage?	0.31	0.22	0.47
5	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?	0.58	0.24	0.18
	Panel B: Landowning farmers (Employers) (N=200)			
6	Do you remember any year when the agricultural wage in this village was less than the wage [for that season] the year before?	0.00	--	1.00
7	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?	0.39	0.25	0.37
8	In non-peak periods, have you ever hired a laborer for agricultural work at a wage below the prevailing wage?	0.05	--	0.95

Notes:
1. The sample is comprised of 196 casual laborers and 200 landowning farmers (i.e. employers) from 34 villages across 6 districts in the Indian states of Orissa and Madhya Pradesh. Respondents were working males aged 20-80.
2. Interviews were conducted July-August 2011.
3. The tabulation of responses for Question 2b is reported below the statement of the question.

For Online Publication

Appendix B: Model Proofs

B.1: Proof of Lemma 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: $\delta \equiv JL^* - \frac{1}{\phi}u\left(\frac{w^*}{p}\right)$. At wage $w_j = w^* - \epsilon$, by the allocation mechanism for workers, 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:

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

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, (3)). 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:

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

Note that:

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

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 (3) and (4).

(i) Suppose firm j raises its wage to some $w_j = w^* + \epsilon$. It follows from the first order condition, (3), 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:

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

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 $\pi_j(w^*, L^*) - \pi_j\left(w^* - \epsilon, L_j^{Avail}\right) \geq 0$.

(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

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

where I define $F(J)$ as the difference in revenue from L^* and L_j^{Avail}. Note that:

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

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

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

Cutting wages to $w^* - \epsilon$ will not be a profitable deviation for any J such that $F(J) - \frac{\epsilon}{J\overline{\phi}}u\left(\frac{w^*}{p}\right) > 0$. 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. ■

B.2: Proof of Proposition 1 (Asymmetric Adjustment to Shocks)

I prove each of the two parts of Proposition 1 in turn.

(i) Define $\widetilde{\theta}_R, = \frac{\bar{w}_{t-1}}{pf'\left(\frac{1}{(J-1)\overline{\phi}}u\left(\frac{\lambda\bar{w}_{t-1}}{p}\right)\right)}$. For $\theta \in \left(\widetilde{\theta}_R, \theta_R\right)$, no firm will deviate from wage offer $\bar{w}_{t-1}$:

(a) Suppose firm j deviates by raising the wage to $w_j > \bar{w}_{t-1}$. It follows from the first order condition, (5), that the firm will demand labor $L_j^{FOC} < \overline{L}$. However, it could have hired L_j^{FOC} workers under wage $\bar{w}_{t-1}$, with a lower wage bill and higher profits. This deviation cannot be profitable.

(b) Suppose firm j deviates by lowering the wage to $w_j \in (\lambda \bar{w}_{t-1}, \bar{w}_{t-1})$. By the firm's first order condition (5), j's labor demand will increase, but the supply of labor available to j will decrease to some L_j^{Avail}: $0 < L_j^{Avail} < \overline{L}\left(\theta, p, \bar{w}_{t-1}\right)$. Then:

$$\begin{aligned}
\pi_j\left(w_j, L_j^{Avail}\right) &= p\theta f\left(\lambda L_j^{Avail}\right) - w_j L_j^{Avail} \\
&< p\theta f\left(\lambda L_j^{Avail}\right) - \bar{w}_{t-1}\left(\lambda L_j^{Avail}\right) && (\textit{since } w_j > \bar{w}_{t-1}\lambda) \\
&< p\theta f\left(\overline{L}\left(\theta, p, \bar{w}_{t-1}\right)\right) - \bar{w}_{t-1}\overline{L}\left(\theta, p, \bar{w}_{t-1}\right) && (\textit{by FOC at } \bar{w}_{t-1}) \\
&= \pi_j\left(\bar{w}_{t-1}, \overline{L}\left(\theta, p, \bar{w}_{t-1}\right)\right).
\end{aligned}$$

This deviation is not profitable.

(c) Suppose firm j deviates by lowering the wage to $w_j \leq \lambda \bar{w}_{t-1}$. Since $\theta > \theta'_R$, the definition of θ'_R above implies:

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

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

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

The profits from cutting to $w_j \leq \lambda \bar{w}_{t-1}$ are therefore 0. This deviation is not profitable.

The first order condition (5) implies that for $\theta \in \left(\widetilde{\theta}_R, \theta_R\right)$, $\overline{L}\left(\theta, p, \bar{w}_{t-1}\right) < \overline{L}\left(\theta_R, p, \bar{w}_{t-1}\right)$. This is because the wage remains fixed at $\bar{w}_{t-1}$, while $\theta < \theta_R$, and $f(\cdot)$ is concave. Since by the definition of θ_R, $J\overline{L}\left(\theta_R, p, \bar{w}_{t-1}\right) =$

$\frac{1}{\overline{\phi}}u\left(\frac{\bar{w}_{t-1}}{p}\right)$, this implies that for $\theta \in \left(\widetilde{\theta}_R, \theta_R\right)$, $J\overline{L}\left(\theta, p, \bar{w}_{t-1}\right) < \frac{1}{\overline{\phi}}u\left(\frac{\bar{w}_{t-1}}{p}\right)$. Thus, there will be excess labor supply in the market.

Finally, note that $\underset{\lambda \to 0}{lim}\ \widetilde{\theta}_R = \underset{\lambda \to 0}{lim}\ \frac{\bar{w}_{t-1}}{pf'\left(\frac{1}{(J-1)\overline{\phi}}u\left(\frac{\lambda \bar{w}_{t-1}}{p}\right)\right)} = 0$.

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

(a) Suppose firm j raises its wage to some $w_j = \overline{w}\left(\theta, p, \bar{w}_{t-1}\right) + \epsilon > \bar{w}_{t-1}$. Since $w_j > \bar{w}_{t-1}$, j's first order condition (5) 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 $w_j = \overline{w}\left(\theta, p, \bar{w}_{t-1}\right) - \epsilon \geq \bar{w}_{t-1}$. (Note that this implies $\theta > \theta_R$). The firm's choice of labor demand at w_j is given by first order condition (5). 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 $w_j = \overline{w}\left(\theta, p, \bar{w}_{t-1}\right) - \epsilon < \bar{w}_{t-1}$. 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 $L_j^{FOC,\lambda} < L_j^{FOC,B}$ because of the assumption in the model that $f'\left(\overline{L}\right) > \lambda f'\left(\lambda\overline{L}\right)\ for\ \lambda < 1$. 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:

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

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:

$$
\begin{aligned}
\pi_j\left(w_j, L_j^{FOC,\lambda}\right) &= p\theta f\left(\lambda L_j^{FOC,\lambda}\right) - w_j L_j^{FOC,\lambda} \\
&< p\theta f\left(L_j^{FOC,\lambda}\right) - w_j L_j^{FOC,\lambda} && (since\ \lambda < 1) \\
&< p\theta f\left(L_j^{FOC,B}\right) - w_j L_j^{FOC,B} && (by\ FOC\ condn\ (3)) \\
&< p\theta f\left(L^*\right) - w^* L^* && (by\ Proposition\ 1\ proof) \\
&= p\theta f\left(\overline{L}\right) - \overline{w}\overline{L} \\
&= \pi_j\left(\overline{w}, \overline{L}\right)
\end{aligned}
$$

Thus, such a downward deviation cannot be profitable.

Since $\overline{w}\left(\theta_R, p, \bar{w}_{t-1}\right) = w^*\left(\theta_R, p\right)$ for $\theta \geq \theta_R$, this implies $\overline{L}\left(\theta_R, p, \bar{w}_{t-1}\right) = L^*\left(\theta_R, p\right)$ because labor demand under the first order conditions (3) and (5) coincides for $w \geq w_R$. As a result, condition (4) implies $J\overline{L}\left(\theta, p, \bar{w}_{t-1}\right) = \frac{1}{\phi} u\left(\frac{\overline{w}(\theta, p, \bar{w}_{t-1})}{p}\right)$ for $\theta \geq \theta_R$. ■

B.3: Proof of Proposition 2 (Ratcheting: Distortions from a Higher Previous Wage)

Following the proof of Proposition 1, define $\widetilde{\theta}_R^{high} = \frac{\bar{w}_{t-1}^{high}}{pf'\left(\frac{1}{(J-1)\bar{\phi}} u\left(\frac{\lambda \bar{w}_{t-1}^{high}}{p}\right)\right)}$. Following equation (6), define θ_R^{low} implicitly as $w^*\left(\theta_R^{low}, p\right) = \bar{w}_{t-1}^{low}$.

By Proposition 1, $\overline{w}\left(\theta, p, \bar{w}_{t-1}^{high}\right) = \bar{w}_{t-1}^{high}$ for all $\theta \in \left(\widetilde{\theta}_R^{high}, \theta_R^{high}\right)$. Since, from Proposition 1, $\frac{\partial \widetilde{\theta}_R^{high}}{\partial \lambda} > 0$ and $\lim_{\lambda \to 0} \widetilde{\theta}_R^{high} = 0$, for λ sufficiently small, it follows that $\overline{w}\left(\theta, p, \bar{w}_{t-1}^{high}\right) = \bar{w}_{t-1}^{high}$ for $\theta \leq \theta_R^{high}$.

First note that for $\theta \in (\theta_R^{low}, \theta_R^{high})$:

$$\begin{array}{rcll} \overline{w}\left(\theta_R^{low}, p, \bar{w}_{t-1}^{low}\right) & = & w^*\left(\theta_R^{low}, p\right) & by\, definition\, of\, \theta_R^a\, and\, Proposition\, 1 \\ & < & w^*\left(\theta_R^{high}, p\right) & by\, Lemma\, 1 \\ & = & \bar{w}_{t-1}^{high} & by\, definition\, of\, \theta_R^b \end{array}.$$

In addition, for $\theta \leq \theta_R^{low}$, $\overline{w}\left(\theta, p, \bar{w}_{t-1}^{low}\right) \leq \bar{w}_{t-1}^{low} < \bar{w}_{t-1}^{high}$, where the first inequality follows from Proposition 1. Together, the above imply that $\overline{w}\left(\theta, p, \bar{w}_{t-1}^{low}\right) < \bar{w}_{t-1}^{high}$ for $\theta < \theta_R^{high}$.

Since for λ sufficiently small, $\overline{w}\left(\theta, p, \bar{w}_{t-1}^{high}\right) = \bar{w}_{t-1}^{high}$ for $\theta < \theta_R^{high}$, this implies: $\overline{w}\left(\theta, p, \bar{w}_{t-1}^{low}\right) < \bar{w}_{t-1}^{high} = \overline{w}\left(\theta, p, \bar{w}_{t-1}^{high}\right)$ for $\theta < \theta_R^{high}$. Then, $\overline{L}\left(\theta, p, \bar{w}_{t-1}^{high}\right) < \overline{L}\left(\theta, p, \bar{w}_{t-1}^{low}\right)$ *for* $\theta < \theta_R^{high}$ by the firm's first order condition (5). ■

B.4: Proof of Proposition 3 (Effect of Inflation on Wage Adjustment)

I state the text of Proposition 3(i) formally:

For any fixed $\theta = \theta'$ *and* $p = p'$ *such that* $\overline{w}\left(\theta', p', \bar{w}_{t-1}\right) = \bar{w}_{t-1} > w^*\left(\theta', p'\right)$,

$$\frac{\partial}{\partial p}\left(\frac{\overline{w}\left(\theta, p, \bar{w}_{t-1}\right)}{p}\right)\bigg|_{\theta=\theta', p=p'} < 0.$$

In addition, $\exists\, \widetilde{p} > p'$ *such that* $\forall p \geq \widetilde{p}$*:* $\overline{w}\left(\theta', p, \bar{w}_{t-1}\right) = w^*\left(\theta', p\right)$.

The first part of Proposition 3(i) states that when there is a wage distortion, real wages will fall as price levels rise. First, note that a change in the price level will shift the θ-interval over which rigidity binds. To make explicit the fact that this interval depends on p, write this interval as $\left(\widetilde{\theta}(p), \theta_R(p)\right)$. Since the rigidity binds at θ' and p', this implies that $\theta' < \theta_R(p')$ by Proposition 1. Suppose $\theta' \in \left(\widetilde{\theta}_R(p'), \theta_R(p')\right)$. For δ sufficiently small, for any $\epsilon \leq \delta$, it will be the case that $\theta' \in \left(\widetilde{\theta}_R(p'+\epsilon), \theta_R(p'+\epsilon)\right)$ by the fact that $\widetilde{\theta}_R(p)$ and $\theta_R(p)$ are continuous in p. Thus, $\overline{w}\left(\theta', p'+\epsilon, \bar{w}_{t-1}\right) = \bar{w}_{t-1}$. As a result, we have:

$$\frac{\partial}{\partial p}\left(\frac{\overline{w}\left(\theta, p, \bar{w}_{t-1}\right)}{p}\right)\bigg|_{\theta=\theta', p=p'} = \lim_{\epsilon \to 0} \frac{\frac{\overline{w}(\theta', p'+\epsilon, \bar{w}_{t-1})}{p'+\epsilon} - \frac{\overline{w}(\theta', p', \bar{w}_{t-1})}{p'}}{\epsilon} = \lim_{\epsilon \to 0} \frac{\frac{\bar{w}_{t-1}}{p'+\epsilon} - \frac{\bar{w}_{t-1}}{p'}}{\epsilon} < 0.$$

If $\theta' \leq \widetilde{\theta}_R(p')$, then similar logic applies: an ϵ increase in the price level, firms will hold the wage fixed at $\bar{w}_{t-1}$ (thereby experiencing an increase in profits). Thus, the real wage will fall with an ϵ increase in the price level.

The second part of the Proposition 3(i) states that a sufficiently large increase in the price will enable the market to achieve the market-clearing real wage. To see this, note that as the price level rises above p', holding the wage fixed at $\bar{w}_{t-1}$, labor supply will fall, while the first order condition (5) implies that labor demand will rise. There will be a $\widetilde{p} > p'$ at which aggregate labor demand will be exactly equal to aggregate supply. This $\widetilde{p}$ is pinned down by the following condition:

$$\widetilde{p}\theta' f'\left(\frac{1}{J\bar{\phi}} u\left(\frac{\bar{w}_{t-1}}{\widetilde{p}}\right)\right) = \bar{w}_{t-1}.$$

Note that at $\widetilde{p}$ and θ', $\bar{w}_{t-1}$ is the market clearing wage. This implies that: $\overline{w}\left(\theta', \widetilde{p}, \bar{w}_{t-1}\right) = w^*\left(\theta', \widetilde{p}\right) = \bar{w}_{t-1}$. In addition, for any $p'' \geq \widetilde{p}$:

$$\begin{aligned}
\overline{w}\left(\theta', \widetilde{p}, \bar{w}_{t-1}\right) &= \bar{w}_{t-1} && by\, definition\, of\, \widetilde{p}. \\
&= w^*\left(\theta', \widetilde{p}\right) \\
&\leq w^*\left(\theta', p''\right) && since\ \tfrac{\partial w^*}{\partial p} > 0 \\
&= \overline{w}\left(\theta', p'', \bar{w}_{t-1}\right) && by\ Proposition\ 1\ since\ w^*\left(\theta', p''\right) \geq \bar{w}_{t-1}
\end{aligned}$$

Thus, $\forall p \geq \widetilde{p}$, $\overline{w}\left(\theta', p, \bar{w}_{t-1}\right) = w^*\left(\theta', p\right)$. In addition, this implies $\overline{L}\left(\theta', p, \bar{w}_{t-1}\right) = L^*\left(\theta', p\right)$ since $\overline{w}\left(\theta', p, \bar{w}_{t-1}\right) \geq \bar{w}_{t-1}$ and also implies market clearing by Proposition 1.

The proof of Proposition 3(ii) follows the same logic as in the benchmark case. By Proposition 1, for any $\theta > \theta_R$, the equilibrium wage corresponds to the market clearing wage (i.e. $\overline{w}\left(\theta, p, \bar{w}_{t-1}\right) = w^*\left(\theta, p\right)$). It is straightforward to verify from equations (3) and (4): $\frac{\partial w^*(\theta,p)}{\partial p} = \frac{w^*}{p}$. Consequently, for any $\theta > \theta_R$, the nominal wage will rise to keep the real wage constant.■

Appendix C: Data Construction

National Sample Survey

The National Sample Survey (NSS) is a nationally representative survey of over 600 Indian districts. I use the rural sample of all the Employment/Unemployment rounds of the NSS (rounds 38, 43, 50, 55, 60, 61, 62, 64, 66, covering the years 1983-2009). Households in each district are sampled on a rolling basis over the agricultural year (July to June). The survey elicits daily employment and wage information for each household member over the 7 days preceding the interview. Since the monsoon is the rainfall shock used in the analysis, I restrict the sample to the Kharif (monsoon) growing season: the months between monsoon arrival and the end of harvesting in January.[46] Agricultural work is identified in the questionnaire as work activity corresponding to agricultural operations; I include all operations that fall within the period of monsoon arrival to harvesting: sowing, transplanting, weeding, and harvesting.[47]

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 compute the daily agricultural wage as paid earnings for casual agricultural work divided by days worked. I use total wage earnings: cash plus in-kind wages. 93% of wage observations in the sample have some cash component. The wage regression results are essentially the same if log cash wages is used as the dependent variable instead of log total wages.

Across years, the Government of India has split districts and regions into smaller units; in order to keep the geographic identifiers as consistent across years as possible, I have manually recoded split districts and regions to maintain the original parent administrative units. 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

[46] February-April is the lean season in rain-fed areas. In areas that plant a second crop during this season, this usually requires irrigation and the monsoon is a less important determinant of labor demand.

[47] In round 61, there is no data specifying agricultural operations. For this round, I identify agricultural work by using the industry code corresponding to agriculture.

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 less precise) results in the regressions. In addition, all regressions use the multiplier weights provided with the data.

World Bank Agriculture and Climate Dataset

The World Bank Agriculture and Climate dataset provides yearly panel data on districts in 13 states over the agricultural years 1956-1987. The unit of observation is a district-year. The wage data were compiled by Robert E. Evenson and James W. McKinsey Jr. using data from the Directorate of Economics and Statistics within the Indian Ministry of Agriculture.

The reported wage variable equals the mean daily wage for a male ploughman in the district-year. 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 each month. For each district-year, the annual wage variable averages over villages and across months in the agricultural year (July to June). The planting months at the start of the agricultural year are weighted more heavily than other months (because field activities are larger in those months). When the data for a male ploughman are not available, wages for a general male agricultural laborer are used instead.

The dataset includes data on 271 districts. I limit analysis to the 240 agricultural districts that grow at least some rice (measured as the districts whose mean percentage of land area planted with rice is at least 0.5%). Since rice is by far the dominant crop in India, districts that do not grow any rice are unlikely to engage in substantial agricultural activity. Performing the analysis with all 271 districts gives similar results, with slightly larger standard errors.

Rainfall Data

Rainfall data is taken from *Terrestrial Precipitation: 1900-2008 Gridded Monthly Time Series* (version 2.01), constructed by Cort J. Willmott and Kenji Matsuura at 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 Census of India.

Consumer Price Index Data

Inflation is computed from the state-wise *Consumer Price Index for Agricultural Labourers in India*, published by the Government of India. Inflation in year t is the percentage change in the state CPI from calendar year t-1 to calendar year t. State-level CPI data is not available before the year 1957. Thus, for the years 1956 and 1957, I use national CPI numbers and use the national inflation rate across the whole country in the regressions. Omitting these 2 years in the analysis has little effect on the findings (Appendix Table 6, Col. 1).