Employment Protection and the Labor Informality of the Youth: Evidence from India

1 Introduction

This paper explores unintended consequences of employment protection laws (EPL), which limit the ability of employers to fire workers. Nearly every country in the world has some form of EPL, which can be a requirement of advance notice, a severance payment, a prohibition on firing, or some combination of these (World Bank 2015). One common argument in favor of these laws is that they reduce income risk in the absence of perfectly functioning insurance markets (Pissarides 2001).

Although there may be benefits, EPL carries the risk of creating distortions in the labor market. For example, a worker may respond to increased job security by reducing her effort level (Ichino and Riphahn 2005). EPL may also introduce more subtle distortions, including a change in the age composition of the labor force (an "age distortion"). The central question of this paper is to ask whether EPL generates an age distortion, and if so, whether there are measurable implications for productivity.

I study these phenomena in India's manufacturing sector. India is an excellent setting to study EPL because India's EPL is among the strictest in the world (World Bank 2008), so the distortions it creates are large and important for the Indian economy. In addition, there is considerable variation in state-level EPL, meaning that it is possible to restrict attention to a single country, ensuring that much of the institutional environment is the same across the data.

India's main labor law is the Industrial Disputes Act (IDA), which requires large plants to obtain government permission before the plants can fire a permanent worker. Contract workers in all plants and permanent workers in small plants (I discuss the size threshold below) can be fired freely. I define workers who are permanent workers in large plants as "formal"; these are the workers who are protected by EPL. One important feature of the law is that it does not apply to workers who have reached retirement age, which is generally

58 years old.

There are two reasons why EPL may lead to an older workforce. The first is that a forward-looking firm is reluctant to hire a young worker if it will not be able to fire her if she turns out to be unproductive, which I call the apprehension effect. Older workers are especially "safe" in India, because firms know there is no risk of an unproductive worker staying on past the retirement age. The second reason that EPL leads to an older workforce relates to what happens if a firm does hire a worker who turns out to be a poor worker. In the absence of EPL, the firm can fire the worker and hire someone else. New hires tend to be young, so this makes the labor force younger. On the other hand, if a firm is disallowed from firing because of EPL, then the worker will remain with the firm, so the labor force will be older. I call this the legacy effect.

First I demonstrate a correlation: in states with stronger EPL, older workers are more likely to be formal. The strength of a state's EPL is calculated by aggregating the ratings of three earlier papers.[1] To argue that stronger EPL causes older workers to be in the formal sector, as opposed to the results being driven by an omitted variable or reverse causality, I consider heterogeneity across manufacturing sectors. The broad strategy is to argue that some manufacturing sectors are more impacted by EPL than others. If EPL causes the formal sector to be older, then we should observe more old formal sector workers in sector-state combinations that have strong EPL and are most affected by EPL. Rajan and Zingales (1998) use similar reasoning to argue that financial development causes economic growth, because countries with strong financial systems have especially strong manufacturing sectors in exactly the sectors that rely heavily on external finance.

Which manufacturing sectors in India are most affected by EPL? Sectors where employers would frequently fire workers if not for EPL are the sectors where EPL matters the most, but it is not possible to observe directly which sectors would have the most fir-

[1] They are Besley and Burgess (2004), Bhattacharjea (2008), and OECD (2007).

ing. The United States is a useful proxy because it has very weak EPL.[2] There is a strong correlation between the rank of involuntary separation rates from one country to another (Micco and Pagés 2006), which provides some reassurance that the rank of separation rates is driven by characteristics of the sector rather than by idiosyncratic country-specific factors.[3] Thus, I argue that EPL causes the shift in jobs from young to old because older workers are especially likely to be formal in strong-EPL states in manufacturing sectors where the involuntary separation rate in the United States is high.

The next question is whether the shift in jobs from young workers to older workers has a measurable effect on the total factor productivity (TFP) of large plants. If the age composition that a plant would choose in the absence of EPL is profit-maximizing, and EPL causes the plant to employ older workers, then EPL likely reduces plants' profits, and its TFP. To examine this question empirically, it is important to first identify which sector-states are most impacted by EPL. I define the "age shift" as the difference in the average ages of the formal sector and informal sectors. I interpret a high age shift, meaning an older formal sector, as evidence that a sector-state is strongly affected by EPL. This could be because the state has strict EPL, the sector has a high involuntary separation rate, or because the sector-state has strong enforcement of EPL.

Among plants large enough to be affected by EPL, there is a negative relationship between TFP and age shift. Smaller plants provide a useful placebo test, and there is no relationship between TFP and age shift for plants that are too small to be affected by EPL, which suggests that EPL reduces TFP. There are two suggestive arguments that the age distortion is one channel through which EPL reduces TFP. First, younger workers have higher education on average, and EPL does reduce the expected education of formal sector workers through the age distortion by 0.15 years. If education is a proxy for individual

[2] I also use the involuntary separation rate in a group of Latin American countries as a robustness check.

[3] Bassanini et al. (2009) also use the involuntary separation rate of the United States as a proxy for the separation rate of a manufacturing sector in the absence of EPL.

productivity, then this is evidence that that EPL reduces TFP through the age distortion. The magnitude is relatively modest effect, but a state with weak EPL compared to other Indian states still has very strong EPL, so a change to truly weak EPL may have a larger effect.

Second, I look at the relationship between EPL and TFP in old and new plants. New plants have no existing employees, so they are not affected by the legacy effect, but are affected by the apprehension effect. Older plants, on the other hand, are affected by both. There is a stronger negative relationship between EPL and TFP in old plants, which is consistent with the hypothesis that the age distortion is an important channel.

This paper connects two branches of the labor literature. The first is a body of literature which shows that EPL has negative effects on the employment prospects of the young.[4] This literature has been concentrated in wealthy or middle-income countries, and my paper is the first to find this effect in India. The second strand of literature contends that EPL reduces TFP.[5] With the exception of Ichino and Riphahn (2005), who show that EPL reduces TFP by creating moral hazard, these papers do not explore the mechanism. I bridge the gap between the two branches by arguing that EPL creates an age distortion, and that EPL reduces TFP by creating the age distortion.

The rest of the paper is organized as follows. Section 2 provides some background information on the relevant legal institutions of India. Section 3 presents a simple theoretical model. Section 4 outlines the data, the empirical strategy, and the results, and Section 5 concludes.

[4] Notable papers in this vein include: Montenegro and Pagés (2004) in Chile, Heckman and Pagés (2001) in Latin America, Skedinger (1995) in Sweden, Esping-Andersen (2002) and OECD (2004) in Europe.

[5] See, for example, Bassanini et al. (2009) in OECD, Okudaira et al. (2013) in Japan, Autor et al. (2007) in the United States, and Dougherty et al. (2013) in India.

2 Formality and EPL in India

In order to be protected under Chapter VB of the Industrial Disputes Act, a worker must meet several qualifications, but if a worker is protected, then it is very difficult for her employer to fire her (Ahsan and Pagés 2007). First, she must be a regular employee, as opposed to a contract worker, who are hired through outside firms rather than being hired directly. Contract workers have become more common during the past several decades, and may be fired by firms without government permission (Chaurey 2015). Employers cannot dodge EPL without consequence by relying entirely on contract workers, because if the principal employer exercises direct control over workers employed through an outside firm, those workers become regular workers and are entitled to the protections of the IDA (Kumar 2010). The courts can also convert contract workers to regular workers if they do the same tasks as regular workers.

Second, workers are only protected if they are in a plant that is sufficiently large. The employment threshold where Chapter VB applies varies by state, because India's constitution places labor laws on the concurrent list, meaning it is under the purview of both the central and state governments. Under the central act, plants with 100 workers or more must receive government permission to fire a regular worker or shut down the plant, but states can increase or decrease the threshold with permission from the central government. Uttar Pradesh has modified the threshold to 300, and West Bengal's threshold is 50. No state changed this threshold or made any other meaningful changes to the IDA during the span of my data (1998 - 2009), so my analysis relies on the interaction of time-invariant strictness of EPL and sector heterogeneity, rather than on intertemporal variation.

Most of the differences between states' EPL is not related to the IDA's employment thresholds. For example, Andhra Pradesh passed an amendment to the IDA in 1987 that extends the notice that must be given to a worker before the terms of her job can be changed, which is a strengthening of the IDA; see Malik (2007) for more details.

Finally, EPL no longer applies once a worker has reached retirement age. If that age is not specified in the contract of a manufacturing worker, the default is 58 years old, and in practice that is almost always the age that applies.

3 Theory

This section will develop a model that illustrates how EPL impacts a firm's decision between an old and a young employee, and the implications for productivity. That main tradeoff is that a firm is willing to hire a slightly less productive older worker in order to preserve flexibility for the next period.

A firm chooses between a young and old employee in every period, but if it hires a young employee, it may be constrained by EPL to retain that employee in the following period. In some manufacturing sectors, the old have comparative advantage relative to the young. For example, old workers may be more productive than young workers in tasks requiring human capital that is built up over a career, while young workers are more effective at physical labor. [6]EPL is less important in manufacturing sectors where older workers are more productive, because firms can hire an old worker, employ her until retirement, and then hire another old worker.[7]

In order to keep the focus on the choice between old and young, I abstract from a number of important issues, such as how a firm chooses its number of employees (and therefore whether or not it crosses the employment threshold to be affected by EPL), how wages are affected by EPL, and the role of competition in the labor and product markets.

[6]It is not important whether young or old workers are more productive in a sector in an absolute sense; what is important is that the difference in productivity between young and old is different across sectors.

[7]Alternatively, the model could be designed so that sector heterogeneity is based on returns to experience within a particular firm, or so the preciseness of the signal of the young worker's ability varied across sectors.

In practice, large firms employ a mix of regular workers and contract workers. A given worker is likely to be more productive as a regular worker than a contract worker, because of the restrictions on the tasks that a contract worker can perform and on the control that managers can exert on a contract worker. In the interest of simplicity, I focus entirely on the regular workers for the purpose of the theory.

3.1 Firms

When firm m is created, I assume that its level of labor L_m is exogenously given, and fixed over time. The focus of this model is the formal sector, meaning that $L_m \geq 100$, because EPL does not impact smaller firms. The l-th worker in the firm in period t has productivity θ_{lt}, and the firm's output in time t is given by the production function:

$$Output_{mt} = \sum_{l=1}^{L_m} \theta_{lt}. \tag{1}$$

The firm's only cost is wages, so the firm's profit in a period is $\sum_{l=1}^{L_m}(\theta_{lt} - w_{lt})$, and its present discounted profit is

$$Profit_m = \sum_{t=0}^{\infty} \beta^t \sum_{l=1}^{L_m} (\theta_{lt} - w_{lt}) \tag{2}$$

Firms and workers are both immobile, in the sense that they cannot choose their manufacturing sector or their state. The wage-setting process will be described below.

3.2 Labor market and timing

In period 0, a risk-neutral firm is created, and it is matched with one young and one old worker for each of its L_m positions. I assume that a worker applies for a specific position at a firm, meaning that if a firm will have L_m employees, it chooses between one young and one old applicant for each position.[8] The employee works and receives a wage, and the firm realizes a profit that is difference between the wage and the worker's productivity.

In period 1, if the firm hired the old worker in period 0, then the worker retires and the firm is in an identical situation that it was in during period 0. It is again matched with one young and one old worker, employs one of them, and realizes a profit. If the firm hired the young worker in period 0, then with probability e, it will be forced to employ her again in period 1 (high e corresponds to strong EPL). In that case, she will retire after period 1, and the firm will once again be free to hire either a young or an old worker in period 2. If the firm is allowed to fire her, then it is free to choose between keeping her and hiring the young worker, meaning that it is the same position as a firm that hired an old worker in period 0. This process continues for an infinite number of periods.

3.3 Productivity and information

A young worker has productivity $\theta \sim U[\underline{\theta}, \underline{\theta}+1]$, but the realization is not observed by the firm. The parameter $\underline{\theta} > 1/2$ represents the lowest possible productivity of a young worker, and is constant across all manufacturing sectors and firms. The firm knows the distributions of all of the variables, and knows that each draw of θ is independent. An old worker has productivity $\theta \sim U[\underline{\theta}-f, \underline{\theta}+1-f]$, where $-1/2 < f < 1/2$ is specific to the manufacturing sector and exogenous for the firm. The bounds on $\underline{\theta}$ and f are chosen to ensure an interior solution, and to guarantee positive productivities. A high value of f means that young workers in the sector are relatively productive, so firing is frequent, while a low value of f means that employers rarely want to fire workers.

I assume the firm observes the old worker's productivity perfectly, because the old employee has a verifiable track record.[9]

[8] If a firm could observe L_m young and L_m old workers and choose the best L_m workers, there would be economies of scale in the matching process.

[9] This assumption could easily be relaxed, since the firm is risk-neutral and the old worker will retire after

3.4 Wages

To describe how a worker's wage is determined, it is important to first describe her outside option. There are many more workers who want formal sector jobs than there are available positions, so I assume that a worker who passes up an opportunity at a formal job ends up in the informal sector. A worker with productivity θ in the formal sector has productivity of $\alpha\theta$ in the informal sector, where $0 \leq \alpha < 1$ is constant across workers, manufacturing sectors, and states. The informal sector is competitive, with no search frictions, and a worker can earn her expected productivity. The information structure and timing in the informal sector is the same as in the formal sector. A young worker's expected productivity in the formal sector is $\underline{\theta} + 1/2$, so her outside option is to work in the informal sector for a wage of $\alpha(\underline{\theta} + 1/2)$. Firms can observe an old worker's productivity in the formal sector, θ, so firms also know that her productivity in the informal sector is $\alpha\theta$.[10]

I assume that when a firm retains an employee, whether because it chooses to or because it has been forced to be EPL, the firm makes a new wage offer. This new wage takes into account the worker's productivity, which has now been revealed. EPL does place restrictions on pay reductions,[11] but in the interest of simplicity, I assume that EPL prevents firing, but does not impact wage setting.

When the formal sector firm has chosen which worker to hire, it has all of the bargaining power, and it makes a take-it-or-leave-it offer to the worker. If it chooses the young worker, it offers a wage of $\alpha(\underline{\theta} + 1/2)$, and if it chooses the old worker, it offers $\alpha\theta$. Hiring the young worker gives the firm an expected profit of $(1-\alpha)(\underline{\theta} + 1/2)$, while hiring the old

the next period; the model is essentially unchanged if the old worker's expected productivity is distributed $\theta \sim U[\underline{\theta} - f, \underline{\theta} + 1 - f]$ instead of her actual productivity.

[10]Human capital is assumed to not be firm-specific, but the results would be the same if human capital were entirely firm specific and the outside option of all workers was some wage w, where $w < \underline{\theta}$.

[11]If it did not, then EPL would never have any bite, as an employer could retain an employee at a wage of zero.

worker gives the firm a profit of $(1-\alpha)\theta$. The firm's present discounted profit is

$$Profit_m = (1-\alpha)\sum_{t=0}^{\infty}\beta^t\sum_{l=1}^{L_m}\theta_{lt} \tag{3}$$

3.5 A firm's decision

Each position is independent of the others, so the firm's problem is to maximize the profits from a single position within the firm. The profit for position l in firm m is,

$$Profit_{ml} = (1-\alpha)\sum_{t=0}^{\infty}\beta^t\theta_{lt} \tag{4}$$

The only decision the firm makes is whether to hire the young worker or the old worker. Every period in which the firm has a choice between the workers is identical, so without loss of generality we can say the firm chooses a threshold $z-f+\underline{\theta}$, where it hires an old worker if the old worker has productivity of at least $z-f+\underline{\theta}$. In periods when it has the choice of employees, the firm chooses the young worker with probability z (it is more convenient to think of the firm as choosing the probability z rather than the threshold $z-f+\underline{\theta}$).[12]

The reason that a firm may hire an old worker with productivity below $\underline{\theta}+1/2$ is to preserve flexibility for the next period. If the old worker has productivity just below $\underline{\theta}+1/2$, then hiring the young worker does maximize expected productivity in the current period, but the firm risks being committed to a low-productivity employee in the next period.

I define the firm's present discounted profit (starting when the firm is not committed to a worker) as a function of z as $V(z)$. If the firm hires the young worker in period 0, her expected productivity is $\underline{\theta}+1/2$ in period 0. With probability e, it must retain the employee, meaning the expected productivity is $(\underline{\theta}+1/2-f)$ in period 1, and then

[12]For example, if $\underline{\theta}=3$, $f=.1$, and $z=.4$, then the old worker's productivity is distributed $U[2.9,3.9]$, and the firm hires an old worker whose productivity is at least 3.3.

the worker retires and the firm is uncommitted in period 2, so it receives $V(z)$ as a continuation value, starting in period 2. If it is allowed to fire her in period 1 (which occurs with probability $1-e$), then it has continuation value of $V(z)$ starting in period 1. Therefore, the discounted sum of expected productivities when hiring the young worker is $(\underline{\theta}+1/2+e[\beta(\underline{\theta}+1/2-f)+\beta^2 V(z)]+(1-e)\beta V(z))$.

If the firm hires the old worker, her productivity is distributed $U[z-f+\underline{\theta}, 1-f+\underline{\theta}]$, so her expected productivity is $\underline{\theta}+((z-f)+(1-f))/2=\underline{\theta}+(z+1)/2-f$. The firm then earns continuation value of $V(z)$ starting in period 1. We know that the firm is free to hire either worker in period 0, so the probability of hiring the young worker in period 0 is z.

The firm's profit as a function of z is

$$\begin{aligned} V(z) = & z(\underline{\theta}+1/2+e[\beta(\underline{\theta}+1/2-f)+\beta^2 V(z)]+(1-e)\beta V(z))+ \\ & (1-z)[(z+1)/2-f+\underline{\theta}+\beta V(z)] \end{aligned} \tag{5}$$

Solving for $V(z)$

$$V(z) = (-1+2f-z-2fz+z^2-ez\beta+2efz\beta)/(2(-1+\beta)(1+ez\beta))+\underline{\theta}/(1+\beta), \tag{6}$$

and maximizing over z yields the optimal choice of z:

$$z^* = \begin{cases} \frac{\sqrt{\beta e+2\beta ef+1}-1}{\beta e} & e>0 \\ 1/2+f & e=0 \end{cases} \tag{7}$$

Note the numerator and denominator are both zero of the top expression are equal to 0 when $e=0$, and it can be verified via l'Hôpital's rule that this expression is smooth at $e=0$. To gain some intuition behind this expression, consider the special case where $e=f=0$.

Old and young workers are equally productive, and the firm is free to fire any worker, so the firm will just choose whichever worker has the higher productivity in every period, so the probability of hiring the young worker, z^*, is equal to $1/2$. Equation (7) indicates that $z^* = 1/2 + f = 1/2$, as expected.

3.6 Individual-level outcomes

The first question is how the likelihood of a young person being hired varies as EPL varies in strictness. For a young person to be hired, the firm needs to be free to choose and then actually choose the young. Based on equation (5), for every period in which the firm is free to choose, it will be committed to the old worker in ez^* periods, meaning that it is free in a fraction $1/(1+ez^*)$ of the periods and committed in $ez^*/(1+ez^*)$ of the periods. Since it chooses the young worker with probability z^* when it has a choice, it will hire a young person with probability $z^*/(1+ez^*)$. The effect of strengthening EPL on the likelihood that a young person is hired,[13] is:

$$\frac{\partial}{\partial e}\frac{z^*}{1+ez^*} < 0 \tag{8}$$

See Appendix 1 for proof. In words, increasing EPL reduces the chance of a young person being hired, because with strong EPL a firm is less likely to be allowed to fire an old employee, and even when it is free to choose, it is reluctant to hire a young person because it knows it is unlikely to be allowed to fire.

Prediction 1: Fewer young workers work in the formal sector in states with strict EPL.

Next, I examine whether EPL has a stronger impact in those sectors where firms would like to fire more often. First, I verify that in a zero-EPL environment, the firing rate is increasing in f. If $e = 0$, then a firm chooses the young worker when the old worker's pro-

[13] Note that z^* is itself a function of e.

ductivity is below $\underline{\theta}+1/2$, which happens with probability $1/2+f$. A worker is fired when the young worker is hired in two consecutive periods, so a worker is fired with probability $(1/2+f)^2$, which is increasing in f, the relative productivity of younger workers.

To test whether EPL has a stronger effect in sectors where firing is more attractive, I look at how the likelihood of hiring a young worker changes with a change in e and f:

$$\frac{\partial}{\partial e \partial f} \frac{z^*}{1+ez^*} < 0 \tag{9}$$

See Appendix 1 for proof.

Prediction 2: EPL depresses a young worker's chance of being in the formal sector more strongly in manufacturing sectors where firms would like to fire workers.

3.7 Firm-level outcomes

The first two predictions will be tested using individual-level data, and there is an analogous prediction on the firm level. Firm profitability is a function of parameters e, f, and β and the choice variable z. I define $\phi(e, f, \beta)$ as the profits associated with the optimal choice of z. We can verify that firm profitability is decreasing in EPL, and especially in high-firing sectors:

$$\frac{\partial}{\partial e}\phi(e, f, \beta) < 0$$

and

$$\frac{\partial^2}{\partial e \partial f}\phi(e, f, \beta) < 0$$

See Appendix 1 for proof. The more profitable firms also have higher productivity per period, which generates the following prediction.

Prediction 3: EPL reduces a firm's productivity, especially in high-firing sectors.

Finally, a new firm and an older firm are impacted differently by EPL. More specifically, a new firm has no existing employees, so it is not impacted by the legacy effect, while an older firm may have a low-productivity employee that it cannot fire. The hiring decisions of both firms are distorted by the possibility that a worker must be retained, so both firms experience the apprehension effect.

A firm which is committed to a worker has expected productivity of $1/2 - q + \underline{\theta}$. A firm which is not has expected productivity of $(z+1)/2 - q + \underline{\theta}$, and since $z > 0$, the uncommitted plant has a higher expected productivity.

Prediction 4: EPL reduces the productivity of older plants more than new plants.

4 Empirics

The model generates four predictions to be tested. Below, I will explain the data sources used, the strategy that I will use to test the predictions, and the results. Finally, I will present some alternate explanations for my results.

4.1 Data

The individual-level data is from the National Sample Survey (NSS) on Employment and Unemployment, which reports a manufacturing worker's age, regular or contract status, the size of the establishment she works in, as well as education, and sex. To classify the level of EPL in each state, I rely on three papers, Besley and Buress (2004), Bhattacharhea (2008), and OECD (2007). The Annual Survey of Industries provides plant-level data necessary to compute total factor productivity (TFP). Finally, the U.S. Displaced Worker Survey and Micco and Pagés (2006) provide measures of the job loss rate in the United States and Latin America, which serves as a proxy for the firing rate in India.

4.1.1 National Sample Survey

The National Sample Survey is carried out by the central government of India, and is a nationally representative survey covering a wide variety of topics. Questions regarding employment are not asked every year, and there have been only two rounds of the survey that ask the respondent how many people work in her place of business. This question is critical for my definition of formality, so I only use data from those years, 2009-2010 and 2011-2012. I pool the data and use year fixed effects to capture firm-invariant year effects. The 2009-2010 round uses the 2004 version of India's National Industrial Classification (NIC-2004), while the latter round uses NIC-2008. Details on the concordance are available upon request.

There is evidence of age heaping in the sample; for example, there are over five times as many self-reported 40-year olds as 41-year olds. To circumvent this issue, I treat all workers between 38 and 42 years old as 40, all workers between 43 and 47 as 45, and so on. Workers whose contracts do not specify otherwise may be fired after age 58, and there is indeed a large decline in formality from the 53 to 57 age category to the 58 to 62 age category. The forces acting on those workers older than 58 are likely different from those acting on younger workers, so I exclude everyone who is 58 and above. Similarly, I exclude everyone who is under 18 because of child labor laws that affect younger workers.

The definition of "formal" varies somewhat depending on the author and the context. I am most interested in which workers are protected by EPL, meaning they must be a regular worker and not a contract worker, and in a plant with at least 100 workers (this threshold is 50 in West Bengal and 300 in Uttar Pradesh). The NSS asks about the size of the establishment where a worker is employed as a categorical response question, and the workers in the NSS are not matched to the plants in the Annual Survey of Industries dataset described below. The highest category provided is 20 or more workers, so I have a noisy measure of whether a worker is in a plant that is truly protected by EPL. I define a worker as formal if she is a regular worker in a plant with at least 20 workers, which is overcounting somewhat.

4.1.2 State-level EPL

In order to classify the strictness of EPL in each of 15 major states, I follow the approach of Gupta et al. (2009; GHK hereafter), who analyze three earlier studies that classify states. The first paper in the group is by Besley and Burgess (2004), and classifies states according to the text of amendments to the IDA that were passed by the state. They classify each amendment passed by a state in year t as pro-worker or pro-employer, and if a majority of amendments in t is pro-worker or pro-employer, then they classify the state as moving in pro-worker or pro-employer direction in year t. A state's level of EPL in year T is defined as the sum of all of the changes in year $1,...,T$, where the change in every year is limited to be $-1,0,$ or 1.

The second paper is by Bhattacharjea (2008), who argues that Besley and Burgess code some amendments incorrectly, and that the way they aggregate amendments is arbitrary. For example, if one state passes two pro-worker amendments in the same year and another passes the same two amendments in different years, then the first state has an EPL of +1 while the second has an EPL of +2. Bhattacharjea presents his own classification of each amendment to the IDA, and also includes judicial rulings that impact how the IDA is applied.

OECD (2007) uses a survey to identify a range of state-level labor reforms, breaking away from the other two studies in terms of methodology. This study encompasses the IDA, as well as the Factories Act and the Contract Labour Act. The authors consider both the statutory laws and the enforcement mechanisms that are in place.

GHK convert each study's rating of each state into a simple strong, weak, or neutral

EPL (-1, +1, 0), so that there are three ratings for each state, and I use the same three ratings for each state. The only way that our methods diverge is how to collapse from three ratings per state to one. Where there are disagreements between ratings, GHK use a majority rules approach, meaning that every state has a score of -1, +1, or 0. One downside to this approach is that it is discards information. For example, all three papers agree that Maharashtra has strong EPL, while only two of the three code Orissa as having strong EPL, but GHK regard them as having the same level of EPL. The minor change that I make to GHK's method is to preserve that information and add the three ratings to arrive at an overall ranking between -3 and 3. In the main specification I treat this as an interval scale, and in a robustness check I consider EPL as a categorical variable.

To see the ranking of each state, please see Appendix Table 1.

4.1.3 Firing rate

My identification strategy depends on an assumption about which manufacturing sectors in India would have a high rate of firing in the absence of EPL. The first proxy that I consider is involuntary job loss rate in the United States, which I calculate based on the U.S. Displaced Worker Survey (DWS). I pool data from 2004, 2006, 2008, and 2010 (the DWS is published every other year). Bassanini et al. (2009) use the same method to calculate a measure of involuntary separation rates in the United States.

The ideal measure would specifically refer to firing, but the DWS includes firing as part of "other," so firing is not directly observable. Job losses that are categorized in the DWS as something other than firing may also be informative about what the firing rate in India would be. For example, if a worker in the United States loses her job and the reason given is "Position abolished," it is possible that a more junior position was created to fill a similar role. The involuntary job loss rate in the DWS is not a perfect proxy for the firing rate in India, but as long as the discrepancy between the two is uncorrelated with the independent variables of interest, the empirical strategy is unaffected.

The DWS provides data on 16 2-digit manufacturing sectors. The only manufacturing sector that is included in the NSS but not the DWS is tobacco, so I drop tobacco throughout the paper. This leaves 20 2-digit manufacturing sectors in the NSS, classified according to the NIC-2004, and I match manufacturing sectors. Where a DWS sector encompasses two NSS sectors, I apply the DWS firing rate to both NSS sectors. Please see Appendix Table 2 for more details.

Using US separation rates as a proxy for which manufacturing sectors are most affected by EPL is an established strategy in the literature, but one natural concern is whether conditions in the United States are informative about India. While Latin America is still considerably wealthier than India, it may provide some reassurance if results are similar using data from Latin American countries. Following Davis and Haltiwanger (1999), Micco and Pagés (2006) define job reallocation as the sum of job creation and job destruction. They calculate job reallocation for eight[14] manufacturing sectors for 18 countries, across the Americas and Europe. This measure is not the same as firing, but it is similar, because industries with frequent firing will also have high rates of job destruction.

In order to construct a Latin American measure of firing for each of eight sectors, I take the average job reallocation rate for the seven Latin American countries with no missing data: Argentina, Brazil, Chile, Colombia, Mexico, Uruguay, and Venezuela. Micco and Pagés also present the correlation in ranks of the job reallocation rate to assess the similarity between different countries, and find that the correlation is quite high. Colombia is the poorest country of the group and therefore the closest in GDP per capita to India, so the correlation in the rank of job reallocation rates between Colombia and other countries is instructive. With the exception of Sweden, the Spearman rank correlation between Colom-

[14] Again, when matching sectors, I apply the firing rate of a broad category to its components. For example, Micco and Pagés present data on paper, printing, and publishing, and I assume that it applies to both sector 21 (paper and paper products) and sector 22 (publishing, printing, and recorded media) in NIC-2004.

bia job reallocation rates and those of each of the 16 other countries is at least 0.3, which is significantly different from 0 at the one percent level.[15] This finding provides some reassurance that the rank of India's firing rates in the absence of EPL would be similar to the job loss measures in the United States and Latin America.

4.1.4 Plant-level data

The main data source to calculate TFP is the Annual Survey of Industries (ASI), from 1998-1999 to 2007-08. The ASI's sampling sector includes all plants that employ at least 20 workers without power, and at least 10 workers with power, and these plants are surveyed every several years. The census sector consists of the larger factories, but the threshold has varied between 50 and 200 over the course of the sample, meaning that factories with at least 200 have been surveyed every year. For more information regarding data issues within the ASI and the sampling procedure, see Bollard et al. (2013) and Harrison et al. (2011).

I use the Levinsohn-Petrin (2003) method to calculate TFP, which is an improvement on using OLS to calculate total factor productivity. It is similar in that it defines as total factor productivity the residual from a Cobb-Douglas regression. It has the advantage that it corrects for the endogeneity generated by the fact that plants can increase their labor in response to a positive productivity shock by using a plant's intermediate inputs as an instrument for the unobserved productivity shock.

To calculate TFP, I need data on output, labor, capital, fuel, and electricity. After dropping all plant-year observations with missing or negative values, I am left with 227,601 observations and 94,037 unique plants. The ASI provides sampling weights for all plants, which again I use throughout.

The ASI lists values in current rupees, so to adjust for inflation I apply industry-specific

[15] Sweden is the only country whose job reallocation ranks are not correlated with the others. Micco and Pagés discuss possible reasons why Sweden is an outlier in this regard but do not reach any conclusions.

deflators to value added using the Wholesale Price Index (WPI). I deflate intermediate inputs according to the WPI associated with that product's five-digit ASICC code. Some inputs do not have an ASICC code listed; for example, capital is deflated using the WPI for machinery and equipment. Dougherty et al. (2011) give a detailed description of the deflating process, and I follow their method.

4.2 Empirical strategy

The first section of the empirics uses individual-level outcomes from the NSS to argue that EPL shifts jobs from young to old workers. In the second section, I calculate how strongly EPL impacts a sector-state using individual-level outcomes, and then examine the relationship between plant-level TFP and the importance of EPL in a sector-state.

4.2.1 Individual-level outcomes

The first question is whether older workers are relatively more likely to be in the formal sector in states with stricter EPL (Prediction 1 in the theory). To test this relationship, leaving aside for now the question of causality, I consider regressions of the form

$$Formal_{ijk} = f(age_{ijkt}, EPL_k, \delta_{jk}, \delta_t, \xi_i), \tag{10}$$

where i indexes individuals, j indexes manufacturing sectors, k indexes states, and t indexes years (there are two years of data). δ_{jk} is a dummy variable that the worker is in sector j and state k, and ξ_i is a vector of characteristics of worker i. The dependent variable is equal to 1 if the worker is a regular employee in a plant that employs at least 20 people.

In the main specification, I use a linear probability model of the form

$$Formal_{ijk} = \beta_1 age_{ijk} + \beta_2 EPL_k + \beta_3 age_{ijk} * EPL_k + \delta_{jk} + \delta_t + \xi_i + \varepsilon_{ijk}, \tag{11}$$

where ξ_i includes dummy variables for every level of education and for gender. I conclude that the evidence is consistent with Prediction 1 if β_3, the coefficient on the interaction term, is positive.

Note that I estimate how EPL shifts jobs from young to old (or vice versa), but I do not estimate whether EPL creates or destroys formal sector jobs. The reason for this is that there is no time variation in EPL_k in my data, and there is a long list of state-level variables other than EPL that could impact the level of formality. I use sector-state fixed effects, which capture any variable that affects the formality of everyone equally in a sector-state (and therefore in a sector or in a state, as well). The variable EPL_k is absorbed by the fixed effects, and is listed above only for clarity.

Shifting jobs from young to old may have important implications for the education of the workforce. Young workers are disproportionately high education, so the impact of shifting jobs from young to old also decreases the average education of the workforce.

This model imposes a linear structure on EPL, meaning that the change from $EPL = -2$ (strict EPL in two indices and neutral in one) to $EPL = -1$ (strict EPL in one index and neutral in two) has the same impact as the change from $EPL = 1$ to $EPL = 2$, a topic that will be addressed in more detail in the sensitivity analysis section.

I follow the common practice of estimating both types of models so that results do not depend solely on either approach, and results are similar in all cases.

I report standard errors that are clustered at the state level to address the possibility of correlated errors within a state and because the variation in EPL occurs at the state level and I have many observations per state (Bertrand et al., 2004). In an additional robustness check, I use the Donald and Lang (2007) estimator.

Some of the potential endogeneity problems can be solved by considering sector heterogeneity, where some manufacturing sectors are more impacted by EPL than others. I rely on the approach of Rajan and Zingales (1998), who test whether financial development causes economic growth by showing that countries with strong financial systems have especially strong manufacturing sectors in exactly the sectors that rely heavily on external finance (measured as those sectors where American firms use more external finance).

I make a similar argument: if EPL causes the shift in formal jobs from young to old workers, we should see that differences in EPL generate larger formality boosts to old workers in manufacturing sectors in which Indian employers would like to fire workers. The United States has some of the weakest EPL in the world, so it serves as a useful benchmark for what would happen in the absence of EPL. I use measures of job losses in the United States and Latin America as proxies for the firing rate in India. Bassanini et al. (2009) uses the same variation to identify the causal effect of EPL in Europe, and Dougherty et al. (2013) employ the same strategy in India.

I test prediction 2 with the following regression:

$$\begin{aligned} Formal_{ijk} = &\beta_1 age_{ijk} + \beta_2 EPL_k + \delta_{jk} + \delta_t + \xi_i \\ &\beta_3 * age_{ijk} * fire_j + \\ &\beta_4 * age_{ijk} * EPL_k + \\ &\beta_5 * fire_j * EPL_k + \\ &\beta_6 * age_{ijk} * EPL_k * fire_j \end{aligned} \tag{12}$$

and conclude there is evidence that EPL causes the different age composition if $\beta_6 > 0$ (note that EPL_k is absorbed by the sector-state fixed effects, and is listed above only for clarity).

4.2.2 Plant-level outcomes

In the first part of the empirical section, I argue that EPL distorts who is employed in the formal sector. In the second part of the paper, I will provide evidence that suggests that this distortion reduces productivity at the plant level.

The two main datasets (NSS and ASI) are not matched, meaning I do not observe the place of employment of a respondent to the NSS or the age profile of a plant in the ASI. I use the previous results to classify sector-states by how strongly plants within them are affected by EPL.

The first option would be to use the same strategy as above and classify the impact of EPL on a sector-state by the interaction of state-level EPL and sector-level firing rate. The direct effects of EPL and firing rate will be captured by state and sector fixed effects, which are important because of the large number of variables that are constant across the state or sector that may influence TFP. One weakness of using the interaction is that there is no variation that is truly at the sector-state level. For example, if enforcement is stronger in some sector-states than others, this will not be captured.

Instead, I infer the impactfulness of EPL by observing the distribution of ages in the formal and informal sectors in the sector-state. If the formal sector is relatively old, then I conclude that EPL is important, whether because of strict EPL in a high-firing sector, or because of particularly high enforcement.

I define the "age shift" as the difference in average age of the formal and informal sectors in the sector-state. This is based on NSS rather than ASI data, so age shift is a sector-state variable rather than a plant or firm variable.

$$\text{age shift}_{jk} \equiv \text{mean age of formal sector}_{jk} - \text{mean age of informal sector}_{jk} \tag{13}$$

The line of causation is that EPL causes a decrease in TFP, but I do not directly observe EPL at the sector-state level, because enforcement is difficult to measure. EPL also causes the age shift, which I can measure, and stronger enforcement will generate a larger age shift.[16] I look at the relationship between age shift and TFP, but I do not attribute any causal relationship between age shift and TFP; instead, age shift and TFP are both impacted by EPL. Throughout the section on plant-level outcomes, a central identifying assumption is that high age shift sector are more impacted by EPL.

First, I will test whether factories in sector-states with high age shift have a lower TFP, which I will take as evidence that indication that EPL does reduce TFP. Plants with fewer than 100 workers provide a useful placebo test, since the main employment laws do not apply to them. To control for the possibility that there is an unobserved sector- or state-level variable that influences TFP, I use sector and state fixed effects, and cluster at the state level. Breaking the sample into plants with more and fewer than 100 workers (and excluding West Bengal and Uttar Pradesh because they have a different threshold for the IDA), I test prediction 3 using this regression:

$$TFP_{ijkt} = \beta_1 * ageshift_{jk} + \delta_j + \delta_k + \delta_t + \varepsilon_{jk}, \tag{14}$$

where i indexes plants, j indexes states, k indexes manufacturing sectors, t indexes years. I conclude that EPL harms TFP if $\beta_1 < 0$ for factories with more than 100 workers and is near zero for factories with fewer.

One possible concern is that larger plants are more productive, and some unobserved variable that is correlated with age shift causes plants to be larger. I control for the log of a plant's labor to address the possibility of economies of scale, and present results above and below 100 workers, with and without the control.

Using individual-level data allows me to conclude that EPL causes a distortion in who is employed in the formal sector. It is natural to think that this creates some negative impact on TFP, and in this portion of the paper I provide evidence that is consistent with

[16] In terms of the theory, more enforcement can be considered an increase in e, which leads to older formal sector workers.

this hypothesis.

There are two broad classes of mechanisms through which EPL reduces productivity. The first group is the mechanisms that do not vary in strength over a plant's lifetime, and the second group is the mechanisms that impact new and old plants differently.

By comparing new and old plants, all with at least 100 workers, I can test whether there is some mechanism operating whose strength varies over the life of a plant. Finding evidence that such a mechanism does impact TFP is consistent with the hypothesis that the distortion of who is employed has an effect on TFP. The overall strategy is to split the sample in new and old plants with at least 100 workers, and estimate the same regression above:

$$TFP_{ijkt} = \beta_1 * ageshift_{jk} + \delta_j + \delta_k + \delta_t, \tag{15}$$

If the legacy and apprehension effects are both important for TFP, then I expect to see a negative relationship between TFP and age shift for both sets of plants, but a stronger negative relationship for the old plants.

The ASI includes data on a plant's first year of operation, so it is possible to calculate how long a plant has operated, but that leaves open the question of how to define "new" and "old." In the body of the paper, I will split the observations equally into new and old, which means that new plants are defined to be 17 years old or less. To show that the results are not dependent on the threshold chosen, in a robustness check I present the same regression with a wide variety of other thresholds.

4.3 Results

In Table 1 (tables are at the end of this document), I present the results from the regression of equation (11). The linear probability model is column 1, and the probit is in column 2.

The coefficient on the variable of interest, the interaction between EPL and age, is positive and significant at the five percent level in both models, and this result is consistent with Prediction 1, which states that more old workers in the formal sector in states with strict EPL.

To give a sense of the magnitude of of an interaction effect, consider the difference in the predicted probability of formality for old and young workers depending on EPL, based on column 1 of Table 1. In the states with the weakest EPL, I predict that a 20-year old worker has a 5.9 percentage point higher probability of formality than a 55-year old, while in a state with the strongest EPL, I predict the 20-year old has an 8.5 percentage point lower chance of formality. Approximately 21 percent of both 20-year olds and 55-year olds are formal across the entire sample, meaning that the effect is substantial, but plausible.

In addition, based on each worker's predicted chance of formality with different levels of EPL, I can calculate the expected level of education in the formal sector at every level of EPL. I predict that moving from the strongest EPL of any state to the weakest would increase the average years of school in the formal sector by approximately 0.15 years. If education is a reasonable proxy for productivity, then this is evidence that EPL reduces TFP by distorting who has a job. The effect is driven by the fact that EPL increases the average age of the formal sector workforce, and younger workers in India on average have more education. It is true that these younger workers have less experience, but the fact that plants who are relatively unimpacted by EPL choose younger workers suggests that education is in fact important.

An increase of schooling by 0.15 years may appear to be a relatively modest effect in terms of magnitude, but the state with the weakest EPL still has very strong restrictions on firing relative to other countries. Even in relatively pro-employer Uttar Pradesh, government permission is still required to fire a worker in a plant with over 300 workers. If a state in India relaxed EPL to the level of the United States or even to Western Europe, it is likely that the gains in education would be significantly larger.

Next, I test prediction 2, which is that the relationship in Table 1 is especially strong in those manufacturing sectors where employers would like to fire workers. A positive coefficient on Age x EPL x Firing suggests that prediction 2 is true. One way to think of this is that an older worker in a high-firing sector in a strict-EPL state is more likely to have a job in the formal sector than an older worker in a high-firing sector in a lax-EPL state, because this is exactly the type of employee who is most helped by EPL.

In columns 1 and 2, I test this relationship using the US firing rate, with linear and probit models, and results for both are positive and significant. With the Latin American firing rate, about 10 percent of the observations are missing because of a lack of firing rate data in some manufacturing sectors. The linear model, in column 3, is positive and significant, although at the 10 percent level, while the probit results are positive and significant at the one percent level.

Moving to the plant-level data, I estimate Equation (14) to test whether plants in sector-states that are most affected by EPL, as measured by the age shift in the sector-state, have a lower productivity (prediction 3). I find there is a negative and significant relationship for the plants with at least 100 workers (column 1), but no relationship for smaller plants (column 2), which is consistent with the hypothesis that EPL reduces TFP. The fact that there is no relationship between age shift and TFP for small plants provides some assurance that there is not some other variable that is invariant within each sector-state that is driving the results. I do find a positive and strongly significant coefficient on log of labor, which indicates that large plants tend to be more productive, but including that variable does not cause a major change to the coefficient on age shift.

In order to discuss the magnitude of this relationship, the first step is to estimate how much a change in EPL impacts the age shift. I compute expected chance of formality based on column 1 of Table 1. If all of India moved from the lowest level of EPL in the sample to the highest level, then I estimate the age shift would increase by 2.6 years.

Based on column 1 of Table 3, we can conclude that moving from the weakest to the strongest EPL causes an increase in the age shift by 2.6, and also causes a decrease in the TFP variable of .021 (2.6 x 7.9 / 1000). Because TFP is measured as the log of productivity, this corresponds to approximately 2.1 percentage points.

Finally, I estimate Equation (14) again, but splitting the sample in a different way to separate mechanisms that do not vary over the lifetime of a plant (such as the apprehension effect) and those that do (such as the legacy effects). I focus exclusively on the plants with at least 100 workers, and divide the sample into new and old plants. In Table 4, I define "old" plants as 17 years. For plants over 17 years, I find a significant negative coefficient on age shift with and without including log labor as a control. For plants under 17 years old, the coefficient on age shift is also negative, but it is not significant. An F-test reveals that the difference between the two coefficients is significant, at the 5% level without controlling for log labor, and at the 1% level when controlling for log labor.[17]

The fact that old plants are more affected by EPL than young plants is consistent with the hypothesis that the legacy effect is important for TFP. The coefficient is negative in all cases, which is what we would expect if the apprehension effect is important for TFP. However, the relationship is not statistically significant. This may reflect the fact that age shift is a noisy measure of EPL.

4.4 Alternative explanations

In this section I discuss some alternate explanations that could also generate the results presented above, and in some cases I present empirical analysis to test their importance.

[17]The comparison of the coefficients is performed by regressing TFP on age shift, fixed effects for year, sector, and state, where the coefficients on all variables are allowed to be different for new and old plants. Then I test for equality of the coefficient on age shift with new and old plants using an F-test.

4.4.1 Individual-level results

One way that the regression in Equation (12) could generate a spurious non-zero result is if some characteristic of sector-states leads to the passage of stricter EPL. For example, suppose that one state has old workers and strong unions in high-firing sectors, while another has old workers and strong unions in low-firing sectors. Unions in the former would have a stronger incentive to spend resources lobbying for stricter EPL, and if successful, then I would estimate a positive coefficient on $age_{ijk} * EPL_k * fire_j$ even if EPL did not cause the change in the age of the workforce. However, consider the identical scenario, but this time the workers are young instead of old. Unions in the high-firing sector would still lobby for stricter EPL, and now I would estimate a negative coefficient on $age_{ijk} * EPL_k * fire_j$. The issue is that strong unions will push for strict EPL whether their members are mostly old or mostly young, because there is value in helping any union member keep her job.

To generate a positive correlation without a causal relationship, we need to assume that union lobby more when their members were older. But if the main goal of the union is to protect its older members and they are able to influence legislation, it is surprising that the changes to EPL that are passed are provisions like making strikes easier or increasing the penalties for unauthorized firing, which apply broadly to all workers. The more logical step to help specifically older workers would be raise the retirement age, but this has not been done.

A related question is how characteristics of a state influence the types of legislation they pass. For example, those states with an older workforce may have been more likely to pass stricter EPL when those laws were being passed (primarily in the 1970's and 1980's). To the extent that these state-level characteristics are persistent, this phenomenon could generate a correlation between older formal sector workers and stronger EPL, even if the latter does not cause the former.

I can test whether this is a significant concern, albeit indirectly. The main question is whether "sunset industries," those which are declining over time, are substantively different from industries that are growing over time. The concern would be that states wtih a larger share of sunset industries would be more inclined to protect older workers. I define a sector's growth over time is defined as the percentage growth in employment between 1999 and 2008, and a state's exposure to sunset industries is the average growth of the sectors they produce, weighted by the labor force in 1999. Table 5 presents the same regression as those in column 1 of Table 1, but the sample is split into states whose production is mostly in slow-growing sectors (column 1), mostly in fast-growing sectors (column 2), and all sectors (column 3). The coefficients on the variable of interest, Age x EPL, is somewhat larger for the states focusing on fast-growing sectors, but this suggests that age leads to formal sector employment more strongly in the fast-growth states, which is the opposite direction from what one would expect if the states heavy in sunset industries are more likely to protect older workers. Table 6 presents analagous results for the regression in column 1 of Table 2. Here the coefficient on Age x EPL x Firing is nearly identical in the two subsamples, which provides some confidence that the results are not being driven by a state's composition of slow- and fast-growing industries.

4.4.2 Plant-level results

Next, consider problems of selection when estimating Equation (14) for plants above and below 100 workers. The concern is that plants' decision to cross the 100-worker threshold is itself impacted by EPL. The most natural version of this story is that in strict-EPL states, only the most productive plants are willing to become large enough to face EPL, but that would lead to a positive relationship between TFP and age shift in large plants, rather than the negative relationship that I find. That said, one way to address the selection issue is to consider plants who are further from the threshold, because a plant far above or far below

100 workers would likely be on the same side of 100 even if EPL were weaker or stronger. I estimate this regression again in Table 8 using thresholds of 50 and 200 workers, and find similar results.

My explanation for the results in Table 4 is that new and old firms are impacted differently by EPL because they are new or old, but there is another possible interpretation. Chapter VB, the most important form of EPL, was passed in 1976, and applied to all of India. A firm entering the market in, say, 1970 may not have anticipated the legal changes, while a firm entering in 1990 could easily observe it. If firms know a priori whether they will be more or less affected by EPL, then we would expect that in 1970 only the less impacted firms would enter the market, which would generate the observed results that older firms are more affected by EPL. In order to test whether this is an important concern, I reproduce Table 4, but among old firms, I include only those formed after 1976. The results, which are presented in Table 7, are substantively the same.

The results in Table 3 and 4 are consistent with the hypothesis that the distortion in who has a job is important for TFP. They also provide evidence against an alternative hypothesis: that the entire mechanism through which EPL reduces TFP is that EPL reduces worker effort and does not impact who has a job. This hypothesis is not consistent with the results in Tables 3 and 4 because it would imply that new and old plants should be equally affected by EPL.

There is at least one other hypothesis that is consistent with the results on new and old plants. EPL prevents plants from responding quickly to changes in demand. For example, suppose a new plant chooses an employment level that is appropriate for the time when it is created. As the optimal level of employment changes over time, the plant cannot adjust downward if EPL is strong, and may have too many workers. Older plants would then be more affected by EPL than newer plants, which is consistent with my findings. It is the subject of future work to disentangle this effect from the impact of changing who has a job.

4.5 Sensitivity analysis

In this section I consider variations of the regressions presented to test for sensitivity. I present results for some of the main tests, and describe the others. Results are available on request.

4.5.1 Individual-level results

In Table 1, I estimate the increased likelihood of being in the formal sector of being an older worker in a strong-EPL state. In Table 2, I test whether the relationship displayed in Table 1 is stronger in those manufacturing sectors where the involuntary job loss rate in the United States is higher.

Here, I modify the regressions that produce Tables 1 and 2 in a variety of ways. First, instead of using the aggregate EPL rating, I use each of the three component ratings (Besley Burgess 2004, Bhattacharjea 2008, and OECD 2007) separately. The results are similar. All coefficients remain the same sign, and while several results lose significance, some become stronger.

In a second set of tests, I treat the aggregate EPL score as a categorical variable rather than a continuous variable. The coefficients follow the broad pattern that would be expected, where the coefficients on the higher levels of EPL are generally larger. The coefficients do not move linearly though, possibly because there are few states in some of the EPL categories.

Next, I estimate each of the regressions in Tables 1 and 2 dropping each state one at a time, and doing the same for sectors. The results stay very similar throughout. I also drop the self-employed, use a wide variety of different fixed effects specifications, and include different individual controls. The results in all cases remain substantively the same.

4.5.2 Plant-level results

In Table 3, I estimate the relationship between age shift and TFP in plants with at least 100 workers and in those with fewer than 100 workers, which the threshold where the main EPL takes effect. One concern is that plants select into the above and below 100 worker categories based on some unobserved characteristic. Plants that are far from the threshold in either direction are more likely to have chosen a size for some reason other than the EPL threshold, so restricting the sample to plants that are far from the threshold should minimize the concern regarding selection. In Table 8, I estimate the same specification as in Table 3, but I change the employment thresholds to 1 to 49 and 200 and above. The significance for the small plants goes from the five percent level to the ten percent level, but the coefficient remains the same sign and similar magnitude.

In Table 4, I test whether new and old plants have different relationships between age shift and TFP. I define "new" plants as those under 17 years old, but since this is an arbitrary cutoff, I present the same results as in columns 3 and 4 of Table 4 (that is, controlling for log labor) for every threshold between 2 and 30 years. For low cutoffs, there is no significant difference between the coefficients, meaning that I do not reject the null that new and old plants are affected equally by EPL. For cutoffs above 10 years, the difference is significant at the 10 percent level, and for cutoffs above 15 years, the difference is significant at the one percent level. One possible reason that I do not reject the null for low cutoffs is that relatively few plants are younger than 10 years old (recall that the median age is 17 years). These results are presented in Table 9.

5 Conclusion

I have presented a theoretical model and empirical evidence that EPL shifts formal sector jobs away from young workers in favor of older workers. This happens because a plant would rather not commit itself to a young worker for future periods, which distorts the hiring decision. Then when the plant does decide to hire a young worker, it will retain her when she is old, even if it would prefer to fire her, and both of these effects raise the age composition of the plant.

In the second part of the paper, I assume that those sector-states that have relatively old formal sectors are the sectors that are most impacted by EPL. Plants in those sector-states have lower TFP, which suggests that EPL reduces TFP. There is a relationship among plants with at least 100 workers, meaning that EPL applies to the plants, but no relationship in the smaller plants. This is a useful placebo test, so that we can rule out the possibility that an unobserved omitted variable is driving the results.

I have also presented evidence that is consistent with the hypothesis that the distortion in who is employed is responsible for at least part of the TFP reduction. I calculate predicted education rates in the formal sector under different EPL schemes, and find that they are lower when EPL is stronger. These results are driven by the fact that EPL prevents younger workers from securing jobs, and younger workers on average have higher education. One limitation of this approach is that education is an imperfect proxy for productivity, especially in tasks that are more dependent on experience.

EPL reduces TFP more strongly in old plants than in new plants. This is what we would expect if EPL reduces TFP by distorting who has a job, because new plants experience only the apprehension effect, while old plants experience both the apprehension and the legacy effect. The result on old and new plants can rule out the possibility that EPL reduces TFP entirely through a mechanism that does not vary over the life of a plant. For example, this result is inconsistent with the hypothesis that the only mechanism is that moral hazard causes effort to decrease by a fixed percentage in every period.

However, there is at least one other possible explanation that is consistent with these findings: that EPL reduces TFP primarily by distorting the number of people employed, rather than distorting who is employed. It is plausible that new plants are closer to the optimal number of employees than older plants, depending on a plant's strategy regarding size, which would generate results consistent with the data, because new firms would be less affected by EPL than older firms. It will be the focus of future work to disentangle these two mechanisms.

6 Acknowledgements

I would like to thank Treb Allen, Amrit Amirapu, Sam Bazzi, Anne Derbes, Eric Werker, Michael Gechter, Lakshmi Iyer, William Johnson, Kavan Kucko, Kevin Lang, Dilip Mookherjee, Peter Murell, Daniele Paserman, Amanda Schmidt, Robert Schwab, Ben Solow, Vidhya Soundarajan as well as seminar participants at Boston University and the Advanced Graduate Workshop on Poverty, Development, and Globalization. I would also like to thank An Yang and Raisa Behal for excellent research assistance.

7 References

Ahsan, Ahmad and Carmen Pagés, "Are all labor regulations equal? Evidence from Indian manufacturing," *Journal of Comparative Economics*, 2009, *37* (1), 62–75.

Bassanini, Andrea, Luca Nunziata, and Danielle Venn, "Job protection legislation and productivity growth in OECD countries," *Economic Policy*, 2009, *24* (58), 349–402.

Besley, Timothy and Robin Burgess, "Can labor regulation hinder employment performance? Evidence from India," *Quarterly Journal of Economics*, 2004, *17* (3), 91–134.

Bhattacharjea, Aditya, "How do Indian firms respond to employment protection legislation?" University of Delhi. Mimeo, 2008.

Bollard, Albert, Peter J Klenow, and Gunjan Sharma, "India's mysterious manufacturing miracle," *Review of Economic Dynamics*, 2013, *16* (1), 59–85.

Chaurey, Ritam, "Labor regulations and contract labor use: Evidence from Indian firms," *Journal of Development Economics*, 2015, *114*, 224–232.

David, H, William R Kerr, and Adriana D Kugler, "Does employment protection reduce productivity? Evidence from US states," *The Economic Journal*, 2007, *117* (521), 189–217.

Davis, Steven J and John Haltiwanger, "Gross job flows," *Handbook of labor economics*, 1999, *3*, 2711–2805.

Dougherty, Sean M, Veronica C Frisancho Robles, and Kala Krishna, "State-level labour reform and firm-level productivity in India," *India Policy Forum*, 2014, *10*.

Esping-Andersen, Gøsta, *Why we need a new welfare state*, Oxford University Press, 2002.

Economic for Center and Policy Research, "CPS displaced worker uniform extracts," various years.

Gupta, Poonam, Rana Hasan, and Utsav Kumar, "Big reforms but small payoffs: Explaining the weak record of growth in Indian manufacturing," 2009. In S. Bery, B. Bosworth, and A. Panagariya (eds.), *India Policy Forum*, Vol. 5. Washington, DC: Brookings Institution.

Harrison, Ann E, Leslie A Martin, and Shanthi Nataraj, "Learning versus stealing: how important are market-share reallocations to India's productivity growth?" *The World Bank Economic Review*, 2013, *27* (2), 202–228.

Heckman, James and Carmen Pagés, "The cost of job security regulation: Evidence from Latin American labor markets," *Economica*, 2000, 1 (1), 109–54.

Ichino, Andrea and Regina T Riphahn, "The effect of employment protection on worker effort: Absenteeism during and after probation," *Journal of the European Economic*

Association, 2005, *3* (1), 120–143.

Kumar, H L, *Practical guide to contract labour regulation & abolition act & rules*, Universal Law Publishing, 2008.

Malik, P, "Industrial law: A manual of central labour and industrial laws incorporating state amendments with rules," *Regulations and Select Notifications*, Lucknow: Eastern Book Company, 2011.

Micco, Alejandro and Carmen Pagés, "The economic effects of employment protection: evidence from international industry-level data," 2006. Inter-American Development Bank, Washington DC.

Montenegro, Claudio E and Carmen Pagés, "Who benefits from labor market regulations? Chile, 1960–1998" in J. Heckman and C. Pagés (eds.) *Law and Employment: Lessons from Latin America and the Caribbean*. Chicago: University of Chicago Press, 401–434.

OECD, "Employment protection regulation and labour market performance," *Employment Outlook 2004*, 61–125.

OECD, "OECD economic surveys: India," OECD Publications, 2007.

Okudaira, Hiroko, Miho Takizawa, and Kotaro Tsuru, "Employment protection and productivity: Evidence from firm-level panel data in Japan," *Applied Economics*, 2013, *45* (15), 2091–2105.

Olley, G Steven and Ariel Pakes, "The dynamics of productivity in the telecommunications equipment industry," *Econometrica*, 1996, *64* (6), 1263–1297.

Pissarides, Christopher A, "Employment protection," *Labour economics*, 2001, *8* (2), 131–159.

Skedinger, Per, "Employment policies and displacement in the youth labor market," Working Paper, 1995.

World Bank, "Doing business 2009: Comparing regulations in 181 economies," World Bank Publications, 2008.

World Bank, "Doing business: Measuring business regulations," World Bank Publications, 2015.

Tables

Table 1: Formality, age, and employment protection legislation

	(1)	(2)
Age x EPL	0.936**	1.075**
	(0.350)	(0.421)
Age	-0.002*	-0.002**
	(0.001)	(0.001)
Male	0.060***	0.073***
	(0.016)	(0.025)
Observations	22897	22897
Model	Linear	Probit

The dependent variable is 1 if the worker is formal and 0 otherwise. EPL is divided by 1000 for readability. State-sector and year fixed effects, and an indicator variable for level of education, are not reported. Probit coefficients are marginal effects at the mean. Standard errors (in parentheses) are clustered at the state level.

Note: * p < .1 ** p < .05 *** p < .01.

Table 2: Formality, age, separation rate, and EPL

	(1)	(2)	(3)	(4)
Age x EPL x Firing (US)	0.084**	0.096***		
	(0.031)	(0.026)		
Age x EPL x Firing (Latin Am.)			0.139*	0.142***
			(0.067)	(0.025)
Age	-0.001	-0.001	0.001	0.002**
	(0.002)	(0.002)	(0.001)	(0.005)
Male	0.060***	0.074***	0.063***	0.049***
	(0.016)	(0.024)	(0.015)	(0.094)
Observations	22897	22897	20755	20755
Model	Linear	Probit	Linear	Probit

The dependent variable is 1 if the worker is formal and 0 otherwise. Age x EPL and Age x Firing are included in the regression but not displayed (EPL x Firing is not included because it collinear with the fixed effects). State-sector and year fixed effects, and an indicator variable for level of education, are not reported. Probit coefficients are marginal effects at the mean. EPL is divided by 1000 for readability. Standard errors (in parentheses) are clustered at the state level.

Note: * p < .1 ** p < .05 *** p < .01.

Table 3: The relationship between TFP and age shift in large and small plants

	(1)	(2)	(3)	(4)
Age shift in the sector-state	-7.894**	1.696	-8.130**	0.665
	(3.760)	(4.349)	(3.619)	(4.208)
Log labor			0.217***	0.235***
			(0.016)	(0.025)
Observations	57897	143965	57897	143965
Plant size	100+	1-99	100+	1-99

The dependent variable is plant-level TFP. The sample is divided between plants with below 100 (no EPL) and above 100 (EPL) workers. Sector, state, and year fixed effects are not reported. Standard errors (in parentheses) are clustered at the state level.

Note: * p < .1 ** p < .05 *** p < .01.

Table 4: The relationship between TFP and age shift in old and new plants

	(1)	(2)	(3)	(4)
Age shift in the sector-state	-3.290	-12.424***	-2.993	-13.732***
	(4.126)	(4.139)	(4.068)	(4.004)
Log labor			0.205***	0.210***
			(0.020)	(0.023)
Observations	29128	28769	29128	28769
Plant size	100+	100+	100+	100+
Plant age	1-17	18+	1-17	18+

The dependent variable is plant-level TFP. Age shift is divided by 1000 for readability. The sample is divided between new plants and old plants, all with at least 100 workers. Sector, state, and year fixed effects are not reported. Standard errors (in parentheses) are clustered at the state level.

Note: * $p < .1$ ** $p < .05$ *** $p < .01$.

Table 5: Formality, age, and employment protection legislation: States producing high- and low-growth goods

	(1)	(2)	(3)
Age x EPL	0.747*	1.122**	0.936**
	(0.319)	(0.410)	(0.350)
Age	-0.002	-0.002	-0.002*
	(0.002)	(0.001)	(0.001)
Male	0.097***	0.040**	0.060***
	(0.025)	(0.014)	(0.016)
Observations	8750	14147	22897
Model	Linear	Linear	Linear
Growth of state	Slow	Fast	All

The dependent variable is 1 if the worker is formal and 0 otherwise. EPL is divided by 1000 for readability. State-sector and year fixed effects, and an indicator variable for level of education, are not reported. States are split into fast- and slow-growth based on their production of fast- and slow-growing sectors. Standard errors (in parentheses) are clustered at the state level.

Note: * p < .1 ** p < .05 *** p < .01.

Table 6: Formality, age, separation rate, and EPL: States producing high- and low-growth goods

	(1)	(2)	(3)
Age x EPL x Firing (US)	0.060	0.065*	0.084**
	(0.038)	(0.030)	(0.031)
Age	-0.003	-0.000	-0.001
	(0.003)	(0.002)	(0.002)
Male	0.095***	0.041**	0.060***
	(0.025)	(0.014)	(0.016)
Observations	8750	14147	22897
Model	Linear	Linear	Linear
Growth of state	Slow	Fast	All

The dependent variable is 1 if the worker is formal and 0 otherwise. Age x EPL and Age x Firing are included in the regression but not displayed (EPL x Firing is not included because it collinear with the fixed effects). State-sector and year fixed effects, and an indicator variable for level of education, are not reported. States are split into fast- and slow-growth based on their production of fast- and slow-growing sectors. EPL is divided by 1000 for readability. Standard errors (in parentheses) are clustered at the state level.

Note: * p < .1 ** p < .05 *** p < .01.

Table 7: The relationship between TFP and age shift in old and new plants: Dropping firms started before 1976

	(1)	(2)	(3)	(4)
Age shift in the sector-state	-3.290	-12.181*	-2.993	-12.792**
	(4.126)	(5.937)	(4.068)	(5.602)
Log labor			0.205***	0.233***
			(0.020)	(0.035)
Observations	29128	12356	29128	12356
Plant size	100+	100+	100+	100+
Plant age	1-17	18+	1-17	18+

The dependent variable is plant-level TFP. Age shift is divided by 1000 for readability. The sample is divided between new plants and old plants, all with at least 100 workers. Firms formed before 1976 are dropped. Sector, state, and year fixed effects are not reported. Standard errors (in parentheses) are clustered at the state level.

Note: * $p < .1$ ** $p < .05$ *** $p < .01$.

Table 8: The relationship between TFP and age shift in large and small plants: Different plant-size threshold

	(1)	(2)	(3)	(4)
Age shift in the sector-state	-7.097*	2.105	-7.891**	0.964
	(3.561)	(4.266)	(3.504)	(4.093)
Log labor			0.281***	0.277***
			(0.021)	(0.028)
Observations	33675	119171	33675	119171
Plant size	200+	1-49	200+	1-49

The dependent variable is plant-level TFP. The sample is divided between plants with below 50 (no EPL) and above 200 (EPL) workers. Sector, state, and year fixed effects are not reported. Standard errors (in parentheses) are clustered at the state level.

Note: * $p < .1$ ** $p < .05$ *** $p < .01$.

Table 9: The relationship between TFP and age shift in old and new plants: different age cutoffs

Cutoff for new/old	Coeff. for new plants	Coeff. for old plants	Prob > F
2	0.83	-8.2	0.104
3	-0.32	-8.14	0.206
4	-1.6	-8.34	0.194
5	0.34	-9.17	0.117
6	-3.04	-8.89	0.303
7	-4	-8.92	0.301
8	-4.44	-8.83	0.379
9	-2.9	-9.78	0.167
10	-3.15	-9.94	0.116
11	-2.72	-10.46	0.093
12	-2.84	-10.57	0.076
13	-3.39	-10.52	0.08
14	-3.28	-10.94	0.041
15	-3.23	-12.22	0.018
16	-2.89	-13.17	0.007
17	-2.99	-13.73	0.007
18	-3.23	-14.26	0.004
19	-3.68	-14.51	0.006
20	-4.03	-14.8	0.004
21	-5.17	-13.08	0.02
22	-5.1	-13.83	0.014
23	-5.39	-14.03	0.017
24	-5.32	-15.08	0.011
25	-5.05	-16.76	0.001
26	-5.23	-16.47	0.002
27	-5.54	-16.14	0.007
28	-5.51	-17.69	0.003
29	-5.64	-18.23	0.004
30	-5.7	-18.58	0.006

Each row of Table 9 corresponds to a regression of the same form as Table 4, but with a different cutoff for when a plant is considered new as opposed to old. See the body of the paper for more details.

Appendix A: Theory

In this appendix I provide details for several assertions made in the theory portion. Recall that e ranges from 0 to 1 and f ranges from $-1/2$ to $1/2$, and β ranges from 0 to 1. The following lemma will be useful:

Lemma: Suppose a smooth function $f(e, f, \beta)$ satisfies two conditions for all $(e, f, \beta) \in (0,1)$ x $(-1/2, 1/2)$ x $(0,1)$: (i) $\lim_{e \to 0} f(e, f, \beta) = 0$ and (ii) $\frac{\partial f}{\partial e} < 0$. Then $f(e, f, \beta) < 0$ for all $(e, f, \beta) \in (0,1)$ x $(-1/2, 1/2)$ x $(0,1)$.

Proof by contradiction: Suppose that (i) and (ii) are satisfied and there exists some $(\hat{e}, \hat{f}, \hat{\beta}) \in (0,1)$ x $(-1/2, 1/2)$ x $(0,1)$ such that $f(\hat{e}, \hat{f}, \hat{\beta}) \geq 0$. Then $f(\hat{e}/2, \hat{f}, \hat{\beta}) > 0$ by (ii), and $f(e, \hat{f}, \hat{\beta}) > f(\hat{e}/2, \hat{f}, \hat{\beta}) > 0$ for all $e < \hat{e}/2$, but this contracts the assumption (i). Therefore there is a contradiction and the lemma is true. $\square$

Claim 1: For all $(e, f, \beta) \in (0,1)$ x $(-1/2, 1/2)$ x $(0,1)$,

$$\frac{\partial}{\partial e} \frac{z^*}{1 + e z^*} < 0 \tag{1}$$

Proof: We know that for $e > 0$,

$$z^* = \frac{\sqrt{\beta e + 2\beta e f + 1} - 1}{\beta e}, \tag{2}$$

so

$$
\begin{aligned}
\frac{\partial}{\partial e}\frac{z^*}{1+ez^*} =&[\beta^2(-(2ef+e))+-4\sqrt{\beta(2ef+e)+1}+4+\\
&2\beta\left(-e(2f+1)\left(\sqrt{2\beta ef+\beta e+1}-2\right)+\sqrt{2\beta ef+\beta e+1}-1\right)]/\\
&2e^2\sqrt{\beta(2ef+e)+1}\left(\sqrt{\beta(2ef+e)+1}+\beta-1\right)^2
\end{aligned} \tag{3}
$$

The task remaining is to prove that this quantity is negative for all valid values of e, f, and β. I define the numerator of equation (3) as $N(e, f, \beta)$. The denominator of equation (3) is always positive, so to prove the claim, it is sufficient to show that $N(e, f, \beta) < 0$.

N is smooth, and it can be verified that$\underset{e\to 0}{lim} N(e, f, \beta) = 0$. That means that showing $\frac{\partial}{\partial e}N(e, f, \beta) < 0$ for all $e, f, \beta \in (0,1)$ x $(-1/2, 1/2)$ x $(0,1)$ is sufficient to show that $N(e, f, \beta) < 0$, which in turn is sufficient to prove the claim.

$\frac{\partial}{\partial e}N(e, f, \beta) =$

$$
\frac{-\beta(2f+1)\left(-4\sqrt{2\beta ef+\beta e+1}+\beta\left(\sqrt{2\beta ef+\beta e+1}+e(6f+3)-1\right)+4\right)}{\sqrt{\beta(2ef+e)+1}} \tag{4}
$$

It is still not immediately clear that this quantity is negative, so I apply the lemma again. I define the numerator of the right-hand side of equation (4) as $M(e, f, b)$. Similar to above, it can be shown that $\underset{e\to 0}{lim} N(e, f, \beta) = 0$. Again, it is sufficient to show that $\frac{\partial}{\partial e}M(e, f, \beta) < 0$ to show that $M(e, f, \beta) < 0$. Taking the derivative gives

$$
\frac{\partial}{\partial e}M(e,f,\beta) = \frac{-(2\beta f+\beta)^2\left(6\sqrt{\beta(2ef+e)+1}+\beta-4\right)}{2\sqrt{\beta(2ef+e)+1}} \tag{5}
$$

This expression is negative. The denominator is positive and the squared term in the numerator is positive. The term in parentheses in the numerator is positive as well (note that $2ef + e > 0$), and there is a negative sign applied to numerator, so the expression is negative. To wrap up, $\frac{\partial}{\partial e}M(e, f, \beta) < 0$, so $M(e, f, \beta) < 0$, so $\frac{\partial}{\partial e}N(e, f, \beta) < 0$, so $N(e, f, \beta) < 0$, and finally, $\frac{\partial}{\partial e}\frac{z^*}{1+ez^*} < 0$ $\square$

Claim 2: For all $(e, f, \beta) \in (0,1)$ x $(-1/2, 1/2)$ x $(0,1)$,

$$\frac{\partial}{\partial e \partial f}\frac{z^*}{1+ez^*} < 0 \tag{6}$$

Proof:

$$\frac{\partial}{\partial e \partial f}\frac{z^*}{1+ez^*} = -\frac{\beta^3(2f+1)\left(3\sqrt{\beta(2ef+e)+1}+\beta-1\right)}{2(\beta(2ef+e)+1)^{3/2}\left(\sqrt{\beta(2ef+e)+1}+\beta-1\right)^3} \tag{7}$$

The denominator is positive, and the numerator is positive as well, because $2f+1>0$. There is a negative sign applied to the whole fraction, so the right-hand side is negative. $\square$

Next, there are two predictions about the profitability of firms. Recall that V

Claim 3: For all $(e, f, b) \in (0,1)$ x $(-1/2, 1/2)$ x $(0,1)$,

$$\frac{\partial}{\partial e}\phi(e, f, \beta) < 0 \tag{8}$$

Proof:

$$\frac{\partial}{\partial e}\phi(e, f, \beta) = -\frac{(2bef+\beta e)\left(\sqrt{2\beta ef+\beta e+1}-3\right)+4\left(\sqrt{2\beta ef+\beta e+1}-1\right)}{2(1-\beta)\beta^2 e^3\sqrt{\beta(2ef+e)+1}} \tag{9}$$

We can disregard the denominator because it is positive. It is straightforward to show that $x(\sqrt{x+1}-3)+4(\sqrt{x+1}-1)>0$ for all $x>0$, and $2\beta ef+be>0$, so the claim is true.

Claim 4: For all $(e, f, \beta) \in (0,1)$ x $(-1/2, 1/2)$ x $(0,1)$,

$$\frac{\partial^2}{\partial e \partial f}\phi(e, f, \beta) < 0 \tag{10}$$

Proof:

$$\frac{\partial^2}{\partial e \partial f}\phi(e,f,\beta) = \frac{2\left(\sqrt{2\beta ef+\beta e)+1}-1\right)+(2\beta ef+be)\left(2\sqrt{2\beta ef+be)+1}-3\right)}{2(\beta-1)\beta e^2(\beta(2ef+e)+1)^{3/2}} \tag{11}$$

The argument is exactly parallel to the one made to prove Claim 3.

Appendix B: Empirics

In appendix table 1, I present the ratings of EPL strength by state. They are based on three papers, Besley and Burgess (2004), Bhattacharjea (2008), and OECD (2007). These papers use different scales, and they have all been converted to a weak (-1), neutral (0), or strong ($+1$) EPL category by Gupta et al. (2009). The last column indicates the sum of the three ratings for each state, and is what I use for an overall EPL rating.

Appendix table 1 presents the EPL ratings for each state for each of the three different ratings, as well as the aggregate rating that I use throughout. See the description in the body of the paper for more information.

Appendix table 2 presents the rank of involuntary job loss rates in the United States and a group of Latin American countries. A low number indicates a low level of job loss. See the body of the paper for more information.

Appendix table B1: EPL ratings by state

State	BB	Bhat.	OECD	Aggregate
Andhra Pradesh	-1	0	-1	-2
Assam	0	0	1	1
Bihar	0	0	1	1
Gujurat	0	0	-1	-1
Haryana	0	0	-1	-1
Karnataka	-1	-1	0	-2
Kerala	-1	0	1	0
Madhya Pradesh	0	0	0	0
Maharashtra	1	1	1	3
Orissa	1	1	0	1
Punjab	0	0	0	0
Rajasthan	-1	0	-1	-2
Tamil Nadu	-1	-1	0	-2
Uttar Pradesh	0	-1	-1	-2
West Bengal	1	0	1	2

Appendix table B2: Rank of involuntary job loss rates by sector

Manufacturing sector	NIC-2004 code	IJLR US	IJLR Latin Am.
Food manufacturing	15	1	9
Textiles	17	18	11
Clothing	18	18	11
Luggage and shoes	19	18	11
Wood products	20	6	13
Paper products	21	7.5	6.5
Publishing	22	7.5	6.5
Coke, refined petroleum	23	2	3
Chemical products	24	4	3
Rubber and plastics	25	13	3
Non-metallic mineral products	26	5	5
Basic metals	27	14.5	1
Fabricated metals	28	14.5	8
Machinery n.e.c.	29	3	-
Office and computing machinery	30	16	-
Electrical machinery	31	9	-
TV and communication	32	12	-
Medical, optical, clocks	33	20	-
Motor vehicles	34	10.5	-
Other transport equipment	35	10.5	-