Contract Labor and Firm Growth in India

Marianne Bertrand  
University of Chicago Booth and NBER

Chang-Tai Hsieh  
University of Chicago Booth and NBER

Nick Tsivanidis*  
University of Chicago Booth

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Abstract

Many observers have pointed to the bargaining power of organized labor, as initially implemented by the Industrial Disputes Act (IDA) of 1947, as an important constraint on growth in India. This act raises the cost of labor and of laying off workers, particularly for large firms with more than 100 workers. Since the late 1990s, large Indian manufacturing firms have increasingly relied on contract workers supplied by staffing companies who are not subject to the IDA. By 2011, contract workers accounted for 36% of total employment of firms with more than 100 workers. At the same time, the thickness of the right tail of the firm size distribution in formal Indian manufacturing plants has increased, the average product of labor for large firms has declined, the volatility of growth rates among large firms has increased, and the probability that large firms introduce new products has risen. We provide evidence in support of the causal effect of the increased supply of contract labor on the relaxation of employment constraints among large establishments following an Indian Supreme Court decision in 2001. We develop a model of firm growth subject to firing costs to quantify the effect of contract labor on TFP growth in Indian manufacturing.

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1 Introduction

Many observers have pointed to the bargaining power of organized labor, as initially implemented by the Industrial Disputes Act (IDA) of 1947, as an important constraint on growth in India. This act raises the cost of labor and of laying off workers, particularly for large firms with more than 100 workers. In particular, the IDA requires firms with more than 100 workers that shrink their employment to provide severance pay, mandatory notice, and obtain governmental retrenchment authorization. The IDA thus potentially constrains growth in two ways. First, the most productive Indian firms are likely to be sub-optimally small. Consistent with this, the Indian manufacturing sector is characterized by a large number of informal firms, a small number of large firms and a high marginal product of labor in large firms (see Hsieh and Olken 2014 for some evidence). Second, the high costs faced by large firms in retrenching may dissuade them from undertaking risky investments, which may be one of the forces behind the low growth over the life-cycle of Indian firms (see Hsieh and Klenow 2014).

In this paper, we present suggestive evidence that the employment constraints on large Indian firms have declined since the early 2000s. First, the thickness of the right tail of formal Indian manufacturing firms has increased. Second, we show that the gap between the average product of labor of large Indian firms vs. that of small firms has declined since the early 2000s while, in contrast, the gap between the average product of capital of large Indian firms vs. that of small firms has remained essentially constant over the same period.

Although these patterns suggest that the regulation of labor has diminished in India, there has actually been little de jure change in the formal regulation of labor (as opposed to Industrial Licensing where reservations for small scale industries have diminished since 1991). We argue that the change in the Indian manufacturing landscape since the early 2000s was not due to a formal change in the IDA, but rather due to a greater reliance on contract workers hired via staffing companies. While staffing companies themselves have to abide by the IDA (like all formal firms), the contract workers they place into their customer firms are not formally employees of the customers. This arrangement therefore provides customer firms with the flexibility to return the contract workers to the staffing company (who then places the workers in another firm) without being in violation of the layoffs and retrenchment rules imposed by the IDA.

While a legal framework for the deployment of contract labor has been in existence since the early 1970s, the staffing model only started booming in the early 2000s. We argue that a decision by the Indian Supreme Court in 2001 (Steel Authority of India Ltd. v. National Union Water Front Workers), which clarified that employers were not required to automatically absorb their contract workers into regular employment if forced to abolish their reliance on such contract work, played an important role in explaining the explosion of contract labor in India, particularly on the intensive margin. We show in the micro-data of Indian manufacturing establishments that the share of establishments with more than hundred workers that relied on contract labor for more 50 percent of their workforce, while stable around 10 percent throughout the 1990s, takes a sharp upturn in the
early 2000s to reach about 30 percent by 2013. Time series evidence on the elasticity of average product of labor to firm size, and firm size, also show sharp breaks in trend that coincide with the 2001 Supreme Court ruling. We also show these post-2001 changes are more pronounced for firms that are located closer to staffing centers (measured in 1990).

There are two main channels through which a greater reliance on contract workers may have changed the formal manufacturing landscape in India. First, the IDA places size-dependent restrictions on the ease of firing workers. When productivity shocks are mean-reverting, the firing cost due to the IDA makes it more unlikely that large firms will change employment in response to a productivity shock. Because these firing costs are reduced for contract workers, employment among large firms that rely more on contract workers should be more responsive to such productivity shocks. Consistent with this channel, the time series evidence shows both increased likelihood of large (more than 10%) employment change at large firms, as well increase in the standard deviation of employment growth among large firms, starting in the early 2000s. Also, using Bartik-style labor demand shocks as well as rainfall shocks at the district level, we show that firms in district where the contract labor share is higher (or districts that are closer to staffing centers) are more responsive to such demand shocks. Second, the availability of contract labor may have reduced the extent to which large firms face a higher marginal cost of labor because of greater unionization and other labor cost pressures disproportionately imposed on large firms by the regulatory environment. Consistent with this channel, we find that, while there is a positive and stable elasticity average cost of labor to firm size prior to 2000 of about .14, this elasticity starts declining in the early 2000s, dropping to .08 by 2013. We show that this decline comes from two separate forces. First, the relative cost of contract labor compared to permanent labor is lower at larger firms and hence the average of cost of labor goes down for larger firms as they tap more into the contract labor pool. Also, we find evidence that the rise in contract labor exerted downward pressures on the wages of permanent workers at larger firms: the elasticity of permanent labor cost to firm size is positive but starts trending down in the early 2000s, especially in districts that are closer to staffing centers.

We corroborate all of these key findings in a firm-year panel that controls for firm fixed effects as well as industry-year specific shocks. We show that a firm’s increased reliance on contract labor is associated with an increase in its size, a decrease in the average product of labor, an increase in employment variability and a decrease in the average cost of labor. We also show evidence suggesting that reliance on contract labor may allow firms to become more dynamic and undertake more risky investment, in that they become more likely to change their product mix.

In the final part of the paper, we develop a model of firm dynamics subject to adjustment costs to quantify the effect of contract labor on TFP growth in Indian manufacturing. We extend the Klette and Kortum (2004) framework and its recent variants (e.g. Acemoglu et. al. 2013, Akcigit and Kerr 2015) by allowing for type-specific variable adjustment costs that are paid whenever firms fire workers to match the context of the IDA. The anticipation of future retrenchment causes large firms to hire a suboptimally small number of workers.
(increasing the average product of labor) and to invest less in innovation (reducing the likelihood they grow by adding new products). The model therefore captures the impact of the IDA on both the cross-sectional and dynamic moments we document in the reduced form evidence. We then estimate the model disciplined by the moments in the microdata to quantify the role of contract labor growth in reducing these adjustment costs and the impact this had on TFP growth. These quantitative results are forthcoming.

2 Institutional Background

2.1 Industrial Disputes Act (1947)

Labor laws in India are covered by a large number of separate Acts setting minimum wages, conditions of work, payment of wages, benefits, workers’ welfare, health and safety provisions, procedures for the resolution of industrial disputes, conditions for hiring and firing workers, and conditions for the closure of establishments. The key piece of labor legislation in India is the Industrial Disputes Act of 1947 (IDA, 1947) which deals with the conditions for hiring and retrenching workers, as well as for the closure of establishments. The IDA specifies the powers of government, courts and tribunals, unions and workers and the exact procedures that have to be followed in resolving industrial disputes.

A 1976 amendment to the IDA made layoff, retrenchment and closure illegal except with the previous permission of the appropriated government for all firms with more than 300 workers. This coverage was subsequently extended in 1982 to all firms with more than 100 employees. Permission to retrench or to close is rarely granted and unapproved separations carry a potential punishment of both a substantial fine and a prison sentence for the employer. Actual compensation for retrenchment is however quite low by international standards: any worker (as defined by the IDA) with more than 240 days of service is entitled to one month’s notice and 15 days of compensation for every year of service at 50 percent of basic wages plus dearness allowance.

The Industrial Employment (Standing Orders) Act also requires firms of more than 100 employees (and in some states 50) to specify to workers the terms and conditions of their employment, while the IDA requires employers to provide Notice of Change (Section 9-A). This requirement states that no employers can effectuate any change in the conditions of service of any worker without giving 21 days of notice. Shifting weekly schedules or days offs without notice could be in non compliance.

The IDA also sets conciliation, arbitration and adjudication procedures to be followed in the case of an industrial dispute. It empowers national or state governments to constitute Labour Courts, Tribunals, National Tribunals, Courts of Inquiry, and Boards of Conciliation. The government has the monopoly in the submission of industrial disputes to Conciliation Boards, Courts, Tribunals or National Tribunals. In industrial disputes originated by the discharge or dismissal of a worker, the court of tribunals can reinstate the work in the conditions they see fit if they deem such discharge unjustified. If the employer decides to pursue the matter in a higher court, the employer is liable to pay the foregone wages during the period of proceeding.
During the seventies and particularly during the eighties, a number of state amendments increased the variability of the labor laws across states (Besley and Burgess, 2004). In most cases, these amendments increased employment protection. They also increased the cost to employers of solving an industrial dispute, although some changes in the opposite direction were also observed. In the nineties the legislative activity mainly came to a halt, with no new amendments in the IDA.

A number of studies have attempted to estimate the effects of labor market regulations on economic outcomes in India. Fallon and Lucas (1991 and 1993) analyze the effects of the 1976 amendment of the IDA, which mandated firms employing 300 or more workers to request permission from the government prior to retrenchment. They find that formal employment for a given level of output declined by 17.5 percent after the 1976 amendment. Also, Dutta Roy (2004) examined the effects of the 1982 amendment to the IDA, which extended the prohibition to retrench workers without government authorization to firms that employed hundred or more workers. Dutta Roy finds evidence of substantial adjustment costs in employment but no evidence that such costs are driven or altered by the 1982 amendment.

Besley and Burgess (2004) exploit the state-level variation that is induced by the state-level amendments to the labor laws. They show that states which amended the IDA in a pro-worker direction experienced lowered output, employment, investment and productivity in registered or formal manufacturing. In contrast, output in unregistered or informal manufacturing increased. Regulating in a pro-worker direction was also associated with increases in urban poverty.

Hasan, Mitra and Ramaswamy (2007) examine whether differences in labor laws explain differences in the way labor markets adjusted to trade reforms. They find that states with more stringent labor regulations (measured as in Besley and Burgess 2004) have lower demand elasticities and these elasticities are less affected by trade reforms. Aghion et al. (2008) argue that pro-worker states benefited less from the industrial reforms launched in 1991.

### 2.2 Contract Labor in India

Restrictions on the use of contract labor have been in place in India since 1970. The Contract Labour (Regulation and Abolition) Act of 1970 regulates the service conditions of contract labor in firms of 20 or more employees. Employers are required to declare the number of contract workers they employ, as well as the nature of the work they do. Contractors and staffing companies who supply contract workers need to be government-licensed. The Act also protects contract workers by mandating welfare amenities (minimum wage, health, safety, pension) and provisions against the delay in wage payment for these workers. However, contract workers do not have the same level of job protection as that granted to permanent workers, and they are also generally not covered by trade unions. Both factors raise the appeal of contract labor for firms, especially for larger firms that are subject to the IDA, or could become exposed to it upon further expansion of their permanent workforce. Indeed, large firms are more likely to be unionized, and more likely to be subject to strikes and other forms
of “labor militancy,” all of which may drive the wage of their permanent workers up relative to smaller firms. Also, because contract workers are not considered “workmen” at the firm they work at under the IDA, their are exempted from the application of severance pay, mandatory notice or retrenchment authorization. Hence, by resorting to contract employment, an employer could bypass some of the most restrictive regulations of the IDA.

And indeed, Section 10 of the Contract Labour Act was meant to limit such use of contract workers as a “loophole” around the IDA requirements. In particular, Section 10 of the Act gives authority to the Government to control the use of contract labor in any establishment. The relevant factors considered are whether contract labor is employed in work which is of perennial nature and whether it is also done through regular employers in those establishments or in other establishment of similar nature. In other words, contract workers are de jure not supposed to be in charge of tasks within a firm that are typically completed by permanent workers in that firm or other firms in that industry, and the Government has the authority to prohibit contract labor at a firm that may use this labor for its “core” operations.

The Contract Labour Act however left vague what would happen to the contract workers at a firm subsequent to the Government issuing a notification under Section 10 banning the firm from using this labor. In particular, there was uncertainty as to whether, subsequent to an abolition notification under Section 10, the employer would be required to automatically absorb the contracts workers into its permanent workforce. While such absorption would seem to be in the spirit of Section 10 (e.g. not using contract labor as a loophole around the IDA) and might have been implicitly assumed, the Act was not explicit.

A 2001 ruling by the Supreme Court of India, which overturned a prior 1997 ruling, lifted this uncertainty. In particular, in its Steel Authority of India Limited v. National Union Water Front Workers judgement (also referred to as the “SAIL” judgement), the Supreme Court ruled that there is no requirement of automatic absorption of contract workers in the permanent workforce subsequent to an abolition notification. In this ruling, the Supreme Court also articulated that all that contract workers could do in the case of abolishment of their work at a firm was to raise a demand for absorption under the IDA before an industrial tribunal. While contract workers might theoretically be able to make a case for absorption in front of such a tribunal if the contract agreement was a “sham, nominal and a mere camouflage,” this process is both complex and time-consuming and there is no possibility of obtaining a stay-order before the tribunal makes a decision (Gonsalves, 2011).

The SAIL judgement has been deemed by various observers as critical in the rise of contract labor in India. As Singh et al. (2016) note: “The regime engendered by these judicial interpretations has made the task of employing contract labour easier and cheaper - in terms of both, hiring as well as ease of firing. One can take a step further and suggest that it is not merely a matter of being able to hire labour more cheaply
but that in the face of no overall change in the law, the use of contract labour by employers can be used as a device to circumvent some of the restrictions imposed by other restrictive labour legislations (such as the Industrial Disputes Act) and labour market institutions (like trade unions).” With the absorption requirement gone, employers may have become more willing to operate in a legal “grey zone” and rely on contract labor for core operations within their firms. In a survey of about 100 Haryana-based manufacturing firms conducted in 2015, Singh et al. (2016) found that the large majority of surveyed firms that use contract workers report having contract and permanent workers work side by side and that a third of the firms that use contract workers report that contract and permanent workers perform interchangeable tasks. Singh et al. (2016) write: “We can thus broadly make the inference that the survey supports the hypothesis that contract workers are not confined to peripheral activities but rather substitute for regular workers in the core tasks of firms.” Anecdotal evidence also suggests that, unlike in the United States where temporary workers often rotate between establishments employers, India’s contract workers often stay in the same job for years. However, we are not aware of any source (survey or data) that would allow us to confirm this anecdotal claim.

Staffing companies do count as “industries” under the IDA and so are supposed to follow all of the provisions therein, including those regarding hiring and firing. In particular, staffing companies have to abide by the retrenchment conditions of the IDA when a contract worker has been on its rolls for more than 240 days. So technically, the contract labor system shifts retrenchment liability from the client firm that is actually using workers to the staffing firm.

A 2014 report by Staffing Industry Analysts, the leading global advisor on contingent work estimates the Indian staffing market to be worth approximately USD 5 billion. While staffing companies also assist firms with permanent recruitment (12% of revenue) and various HR solutions (13% of revenue), temporary staffing (e.g. contract labor) constitutes the bulk of their business (75% of revenues). As of 2012, the three largest staffing companies in India were Adecco, Teamlease and Randstad and accounted for about 15% of the total market. The market share of the top ten staffing companies was about 26%. Staffing industry analysts estimate that 1.3 million contract workers were employed in the organized sector as of 2014 and predict that it will swell to 9 million workers in the next 10 years. Staffing companies charge a tax to firms that rely on their services on a monthly basis. The effective service tax rate is about 12.4%.

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3This service tax is actually composed of three components: 1) A flat 12% service tax levied on the total value of taxable services. The value of taxable services includes the total compensation paid to the contract workers (including benefits such as providend fund payments and health insurance) and the administrative fees; 2) a 2% “Education Cess” tax which is levied on the payable service tax calculated from (1); and 3) a 1% “Senior and Higher Education Cess” tax which is levied on the payable service tax calculated from (1). For example, consider a firm that hires five contract workers who are each paid Rs. 5000 in combined total compensation per month, and the staffing firm monthly administrative fee is Rs. 500 per contract worker. The total value of taxable services will be Rs. 27,500 (25,000 + 2,500). The firm will pay Rs. 3,300 for the flat 12% service tax. 2) Rs. 66 for the 2% Education Cess (3,300*.02). 3) Rs. 33 for the 1% Senior Cess (3,300*.01). The firm’s total tax liability for this month will be Rs. 3,399. For this month, the staffing company will bill the firm for a total of Rs. 30,899 (27,500 in services + 3,399 in taxes. The Indian government has announced increases to the service tax as part of their proposed 2015 budget. The government is also considering levying an additional service cess tax of up to 2% to pay for its “Clean India” campaign.
Despite various observers’ claim of how the SAIL judgment changed the contract labor sector in India, we are not aware of any research trying to quantify this change, and its implications for the formal Indian manufacturing sector. There are few empirical studies to date on the determinants of the rise of contract labor in India. In an industry-state-year panel, Sen et al. (2010) find that a positive relationship between import penetration and the share of contract workers; they also find that pro-worker legislation and greater bargaining power of permanent workers (as proxied for by the lockout-to-strike ratio or union density) increase the share of contract workers.

3 Motivating Facts

3.1 Data

Our primary source of micro-data on Indian manufacturing is the Annual Survey of Industries (ASI) conducted by the India’s Statistical Office (NSSO). The ASI is a census of formal Indian manufacturing establishments with more than 100 workers and a random survey of formal firms with less than 100 workers. Between 1998 and 2013, the ASI provides establishment identifiers that allows one to exploit the panel dimension of the data. We were also able to access a version covering earlier years, allowing us to construct a plant-level panel between 1993 and 2013. For certain results, we augment this with earlier waves of the ASI between 1985 and 1993 that lacked plant identifiers. Unfortunately, district identifiers are only provided in the ASI until 2009.

The key variables we use are value-added, employment, labor compensation, book value of capital, main industry of the establishment, and the geographical district. Importantly, the ASI provides information on workers directly employed by the establishment and workers hired through contractors (hereafter referred to as “full-time” and “contract” workers). In all years the wages, bonuses and benefits to all workers are reported, but the breakdown between full-time and contract workers are provided only in certain years. We also use the information in the ASI on the detailed outputs produced by the establishment and inputs used by the establishments. The unit of observation is the establishment. The ASI does not provide firm identifiers so we cannot group establishments into firms. The ASI collects data over the fiscal year, which runs from April 1 to March 31 of the following year. When we refer to a year, we refer to data collected between April 1 of the year and March 31 of the following year (e.g., 2011 refers to data collected over the 2011-2012 fiscal year). Finally, we crosswalk district and industry codes across years to generate consistent units across our sample.

We supplement the ASI with a number of additional data sources. First, we use the Economic Census. The 1948 Factories Act requires that establishments with more than 20 workers have be formally registered (the threshold is 10 or more workers if the establishments uses electricity). One third of the plants with less than 100 workers were sampled in the ASI prior to 1994. After 1994 the sampling probability of small plants (less than 100 workers) is about one-seventh. Workers here “include all persons employed directly or through any agency whether for wages or not and engaged in any manufacturing process,... the repair and maintenance or production of fixed assets or for generating electricity or producing coal, gas etc”.

We thank Hunt Alcott for helping us access this data.

Wages by worker category are provided between 1998 and 2013, while bonuses and benefits are reported from 1998 until 2007.
which reports employment across the universe of establishments in India in 1990, 1998, 2005 and 2013. This reports the number of workers, industry and each district of each plant. Second, we use rainfall data from the University of Delaware, which provides monthly rainfall data for geographic gridpoints at 1/2 degree intervals (Willmott and Matsuura 2012). We use this to measure total annual rainfall by district. Third, we use measures of state-level labor regulation from Besley and Burgess (2004) and industry-level reforms occurring between 1985 and 1997 from Aghion et. al. (2008).

3.2 Trends in Indian Formal Manufacturing during the 2000s

We now use the ASI microdata to document 4 trends that have occurred in Indian manufacturing in the 2000s.

**Fact 1. The right tail of the firm size distribution has thickened.**

This is shown in Figure 1 which plots the distribution of employment by firm size in 2000 and 2013, measured as the number of non-managerial workers. There has been a clear thickening of the right tail over the period: every size bin above around 50 employees contains more mass in the later year.

**Fact 2. The average product of labor has declined for large firms.**

Figure 2 plots the relationship between the average product of labor and firm employment separately for the years 2000 and 2013. We define average product of labor as value added over total non-managerial workers. We first regress average product of labor on industry and year fixed effects and then non-parametrically regress the residualized average product of labor on plant employment. As previously documented (e.g. Hsieh and Olken (2015)), this relationship is upward sloping, with larger firms having a greater average product of labor.

Interestingly, this relationship changed during the 2000s. In particular, in 2000 there is a distinct increase in slope starting around the 100 workers mark, yet by 2013 this became much more muted. In other words, while larger firms still have greater average product of labor than smaller firms in the more recent year, the difference in average product of labor by firm size has become smaller than it was in 2000.

**Fact 3. Employment dynamism has increased amongst large firms.**

In Figure 3, we assess how the relationship between the standard deviation of employment growth and firm size changed between 2000 and 2013. The plot shows that while the dispersion of employment growth has remained fairly stable for small establishments with less than 50 workers, employment dynamism for larger plants saw a pronounced increase over the period.

**Fact 4. The use of contract labor has spread, especially amongst large firms.**

In panel (a) of Figure 4, we plot the non-parametric relationship between the probability of hiring any contract labor and firm non-managerial employment, separately for 2000 and 2013. There are two key takeaways from this figure. First, across all firm sizes, the share of firms relying on any contract labor has been
increasing. While about 19.9 percent of firms used any contract labor in 2000, this share had increased to 26.7 percent by 2013. Second, the rise in the use of contract labor has been especially pronounced among firms that employ 100 workmen or more. Close to 65 percent of firms at the 1000 employees mark use some contract workers in 2013, compared to only about 45 percent in 2000.

Panel (b) shows that these changes are even more striking when we assess the share of firms that rely on contract workers for a large portion of their operations. In particular, the figure plots the non-parametric relationship between the probability that contract workers represent at least 50 percent of total non-managerial workers and firm non-managerial employment, again separately for the years 2000 and 2013. Among smaller firms, there has been no discernable increase in the share of firms where contract labor is at least 50 percent of the workforce. In contrast, this rise has been dramatic among larger firms. Around the 50-100 employee mark, the share of firms where contract labor is at least 50 percent of the workforce has gone from about 20 to 30 percent; around the 1000 employee mark, the share has gone from less than 15 percent to nearly 45 percent.

4 Did the Rise in Contract Labor Free up Firm Growth?

The patterns documented above show that there has been a thickening in the right tail of the firm size distribution and a decline in the gap in average product of labor between large and small firms in the formal Indian manufacturing sector since 2000. This period has also been characterized by a sharp increase in the reliance on contract labor among the larger firms in the sector. In this section, we propose 3 approaches that exploit the finer year-to-year variation in the ASI data to argue that these trends are not merely contemporaneous, but are in fact related.

4.1 The SAIL Event

The SAIL judgement in 2001, by freeing up the use of contract workers, may have weakened the constraints large firms that are subject to the IDA faced relative to smaller firms. Under this hypothesis, we expect the year 2001 to mark a break in trend for the key patterns documented under Section 3.

We start by showing that there was indeed a sharp increase in the use of contract labor right after the SAIL event, in particular on the intensive margin for firms that are subject to the IDA Panels (a) and (b) of Figure 5 provide this evidence. Consider panel (a) first. We regress a dummy for whether a firm is hiring any contract labor on year dummies interacted with firm size indicators: a dummy for whether the firm has between 100 and 500 workmen and a dummy for whether the firm has more than 500 workmen (having less than 100 workmen being the missing category). Also included in the regression are industry and year fixed effects. We then plot the estimated firm size coefficients for each year, as well as the 95% confidence intervals. Panel (a) shows that larger firms have always been more likely to rely on some contract labor and this greater reliance has been growing over time. While there might be a slight increase in this trend starting in 2001, it is not a sharp break.
Panel (b) replicate the same exercise as panel (a) but focus on whether contract labor represents at least 50% of a firm’s non-managerial labor. The shows that such intensive reliance on contract labor has always been more prevalent among larger firms but that this difference, while quite stable throughout the 1990s, started to increase sharply after 2001. That such a break in trend around the SAIL judgement would be most visible on the intensive margin may not be surprising. The threat of automatic absorption, which SAIL lifted, might have made firms particularly reluctant to hire large numbers of contract workers.

The fact that it is firms that are subject to the IDA that were most responsive to the SAIL judgement on the intensive margin is consistent with the view that these firms disproportionately had to gain from accessing this pool of workers because it freed them from some of the IDA constraints. This view is supported in the two remaining panels in Figure 5, where we replicate panel (b) but separate states with different labor regulations according to the Besley and Burgess (2004) measure. It is apparent that the reaction to SAIL among IDA-subject firms was greater in pro-worker states (panel (c)) than it was in pro-employer states (panel (d)).

Having established the empirical relevance of the SAIL judgement for the increase in the size of the contract labor system in the Indian manufacturing sector, we now propose to assess whether the timing of the changes in the firm size distribution, and elasticity of average product of labor to firm size documented above also coincide with the SAIL case.

Figure 6 plots the trend in the 50th, 75th, 90th and 95th firm size percentiles between 1983 and 2013. This figure confirms an impressive and sustained growth in the upper percentiles starting around SAIL. The 90th and 95th percentile of firm size, while if anything smaller in 2000 than in 1985, have grown steadily since 2001. The 95th and 90th percentile firms have about 30 percent larger employment in 2013 compared to 2000. In the Appendix, we show that plant size distribution was essentially unchanged in the services industry over the same period.7

Panel (a) of Figure 7 plots the elasticity of the average product of labor with respect to non-managerial employment between 1985 and 2013. We regress log average product of labor on log employment interacted with year dummies, as well as a full set of industry and year fixed effects to control for compositional changes. We then plot the coefficients on log employment in each year. The elasticity shows a persistent increase between 1985 and the early 2000s, but starts to decline after 2002. In Appendix Figure B.3, we provide evidence that the changing relationship between the average product of labor and plant size is qualitatively similar if we measure labor inputs using total labor costs (wages plus bonuses and benefits). In panel (b) of Figure 7, we repeat the exercise for the average product of capital.8 In contrast to the patterns for the average product of labor elasticities, we see the relationship between the average product of capital and plant size was decreasing the early 1990s. Unlike in panel (a), we do not observe a break in trend around the SAIL event.9

7While the IDA as a whole applies to all sectors, section 5 which covers the majority of restrictions on retrenchments applies only to manufacturing factories, mines and plantations with 10 or more workers.
8We define capital as the average of opening and closing book values of assets at the beginning and end of the financial year.
9Appendix Figure B.2 confirms that the relationship between average product of capital and firm employment has not changed much
We hypothesize that the increasing average product of labor elasticity during the 1990s reflects the difficulties firms had in increasing employment in response to newly liberalized markets as India deregulated over the period (Hasan, Mitra and Ramaswamy, 2003). Appendix Table A.1 provides some support for this hypothesis. In particular, we examine in that table how the relationship between average products and plant size evolved between 1985 and 1997 within industries as they liberalized. To do so, we regress the average product of labor or capital on plant size, a measure of reform in the industry and their interaction. In odd columns the reform measure is a dummy equal to one if the industry has delicensed, while in even columns it is the fraction of products open to automatic approval of FDI. Both measures are from Aghion et. al. (2008). The results in the first two columns suggest that the elasticity of the average product of labor to plant size increased substantially as industries either delicensed or opened up to increased FDI. In contrast, we see no relationship between changes in the relationship between the average product of capital and plant size in response to delicensing, and a sharp decrease in this relationship as industries open up to FDI. These findings support our belief that the liberalization during the 1990s increased the ability of large firms to access capital, but left them struggling to hire the workers they needed to take advantage of new growth opportunities.

Overall, the time-series analysis around the SAIL event suggests that the 3 facts about the Indian manufacturing sector that motivated our analysis (increase in the right tail of size distribution, decrease in the gap in average product of labor between large and small firms, increase in the use of contract labor among large firms) are related. The sharp increase in the reliance on contract labor in IDA-contrained firms (especially on the intensive margin) around SAIL coincides with the timing of the increase in firm size and of the decline in the elasticity of average product of labor to firm employment.

4.2 Heterogenous Effects of SAIL

A clear limitation of the SAIL event analysis above is its pure reliance on time-series variation in the aggregate data. To address this limitation, we exploit variation across firms in their ease of access (proximity) to contractors and staffing companies. As discussed above, the Contract Labor Act requires that firms access contract workers through government licensed contractors or staffing companies. It is therefore possible that the SAIL shock we identified in the time series was larger for firms that were located geographically closer to such staffing centers, allowing us to combine time series with cross-sectional variation for better identification.

To proceed, we rely on the 1990 Economic Census to construct for each district in India a measure of how proximate that district is to staffing employment in 1990. While this exercise could also be completed in the 1998 Census, we prefer the 1990 Census to minimize concerns about endogeneous location of staffing centers between 2000 and 2013, and that this true for both larger and smaller firms.

10 Under industrial licensing “an industrial license was required to establish a new factory, significantly expand capacity, start a new product line, or change location...this allowed the government to allocate plan production targets to firms.” (Aghion et. al. (2008)). The vast majority of reforms occured between 1985 and 1991. The Aghion et. al. (2008) data covers 1980-1997, so we use as our sample 1985-1997 when our two datasets line up.
to variation in economic conditions across districts over the 1990s, an active period of policy reforms in India. In particular, we construct a distance-weighted sum of a district’s access to staffing employment in 1990 as

$$ Staffing_d = \sum_{k \neq d} e^{-\kappa \text{dist}_{kd}} L_{\text{Staffing}}^{k,1990} $$

(1)

where $\text{dist}_{kd}$ is the number of kilometers between the centroids of districts $d$ and $k$, and $L_{\text{Staffing}}^{k,1990}$ is the number of workers employed by staffing firms in district $k$ in 1990. The decay parameter $\kappa$ controls the rate at which the weight on surrounding staffing employment decays with distance. We assign a value of 0.0075 to this decay parameter. Consider, for example, that the average distance between all districts in Maharashtra is 358km with a minimum of 32km and maximum of 891km. With $\kappa = 0.0075$, this implies a weight of 0.06 on the average apart and 0.001 on the furthest apart in the state. Note that we exclude own-district staffing employment to remove the most immediate source of endogeneity. We use a spatially weighted sum rather than the staffing employment within a district to capture that, although most districts in 1990 lacked any staffing establishments, those close by still had access to these firms and the industry as a whole radiated outwards from these initial clusters over time.  

Appendix Table A.2 correlates this district-level staffing measure in 1990 to other district characteristics in 1990. Districts close to more staffing employment in 1990 tend to have more overall employment and a greater share of manufacturing in both total and formal employment. However, these districts look balanced in terms of other characteristics such as average firm size (in the ASI) and the share of firms younger than 5 (a proxy for the rate of firm entry). Importantly, there are no significant differences in the difference in APL or full-time worker wages between large and small firms. This supports the hypothesis that the initial growth of the staffing industry did not occur in locations with high demand for their services from manufacturing plants.

Table 1 assesses whether the increase in the use of contract labor after SAIL was larger among firms located in districts that were more proximate to staffing employment. In particular, we regress use of contract labor (any - columns 1 and 2; 25 percent of the workforce or more - columns 3 and 4; 50 percent of the workforce - columns 5 and 6) on a Post-SAIL dummy interacted with 1990 district-level staffing. Each regression includes district fixed effects, industry-year fixed effects and state-year fixed effects. Also, given the findings in Appendix Table A.2, we additionally include as controls in even columns interactions between year dummies and a vector of 1990 district level controls.  

In all columns, as expected, we see that the 2001 SAIL shock to staffing employment we had identified in the time series is more pronounced in districts that are closer to staffing centers. The point estimates are essentially unchanged when we allow for different time effects across baseline district conditions, which suggests that

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11 Additional details are provided in the appendix.
12 We define formal employment as that occurring in establishments with more than 10 workers.
13 These 1990 district level controls include: log average manufacturing firm employment, the share of young firms (less than 5 years old), log district total employment, the manufacturing share of district employment, and the manufacturing share of formal employment.
the interaction term of interest is unlikely to be picking up on other differential changes over time by district-baseline conditions that are correlated to their proximity to staffing centers in 1990.

Given these results, we now proceed with Table 2 where we study how firm level outcomes changed after SAIL for firms with different exposure to staffing. Each cell in Table 2 corresponds to a different regression and reports the estimated coefficient on the interaction term between the Post SAIL dummy and the 1990 district-level staffing exposure measure. Controls in column 1 include district fixed effects, industry-year fixed effects and state-year fixed effects. Column 2 adds interactions between a Post SAIL dummy and surrounding employment in 1990\textsuperscript{14}, while columns 3 and 4 add firm and district controls respectively (each interacted with a post SAIL dummy).

Overall, the findings in Table 2 tend to reinforce our interpretation of the time series as evidence of a causal effect of the rising reliance of contract workers on the firm outcomes of interest. In particular, we find that firms with greater exposure to staffing in their district experienced higher employment after 2001 (row 1), as well a decline in their average product of labor (rows 2 and 3) though this effect is slightly more precise when proxying for labor inputs using total labor costs (wages, bonuses and benefits).\textsuperscript{15}

### 4.3 Firm-Year Panel Analysis

Recall that from 1993 on, the ASI data includes plant identifiers. Table 3 exploits this panel structure of the data to study changes in firms outcomes when these firms start using contract labor. As above, we consider three measures for use of contract labor, spanning the extensive and intensive margins: any (columns 1 and 2); contract labor accounts for 25 percent or more of the workforce (columns 3 and 4); and contract labor accounts for 50 percent or more of the workforce (columns 5 and 6). Each cell in the table corresponds to a different regression and reported in the cell is the estimates coefficients on the contract labor use variable. All regressions control for state-year fixed effects and industry-year fixed effects.

Odd columns illustrate that there is, as expected, clear selection in the use of contract labor across firms. In particular, in these columns, we restrict the sample to two groups of establishments. First, we keep all plants which never hire contract labor (according to the relevant measure of contract labor for that column). Second, we add observations from establishments which at some point hire contract labor but only from the years before they first hire workers through contracting. We then assign a value of 0 to the contract labor use variable to firms that never use contract labor over the sample period, while we assign a value of 1 to firms that use contract labor (any; 25 percent or more; 50 percent or more) at any time during the sample period. It is apparent that firms that will rely at any point on contract labor are larger; they also have higher average product of labor and higher average labor cost. Firms that will use contract labor at any point also appear more dynamic in their employment (lower likelihood of being in the inaction range and higher absolute employment growth rate).

\textsuperscript{14}We construct this using the same measure as in (1), but using total employment instead of staffing employment.

\textsuperscript{15}See the note in Appendix Figure B.3 for a precise definition of APwL.
In the background in these selection patterns, even columns in Table 3 restrict the sample to the set of firms that use contract labor at any point in time, whether or not they use contract labor in a particular year. We then assess changes within firms associated with the use of contract labor by including firm fixed effects. The findings in these columns are broadly consistent with those emerging from the SAIL analysis. Firms grow in size when they use contract labor, whether we define use of contract labor on the extensive (column 2) or intensive margin (columns 4 and 6) (row 1). These firms also experience a drop in the average product of labor after hiring contract workers (rows 2 and 3).

We complement this firm-year panel data analysis with event studies that allow us to more carefully study the evolution of these key outcomes in the years that precede and follow the first hiring of contract labor. In particular, we run the following event study specification:

$$Y_{it} = \sum_{\tau=\tau}^{\tau} \beta_{\tau} \mathbb{I}\{\text{Years Since First Hire}_{it} = \tau\} + \alpha_i + \gamma_{kt} + \gamma_{st} + \gamma' X_{it} + \epsilon_{it}. \quad (2)$$

Here $\alpha_i$ is a plant fixed effect, $\gamma_{kt}$, $\gamma_{st}$, and $X_{it}$ are industry-year and state-year fixed effects and a quadratic in firm age, and $\mathbb{I}\{\text{Years Since First Hire}_{it} = \tau\}$ is a dummy equal to one if year $t$ is $\tau$ years from when the establishment first hired contract labor. $\beta_{\tau}$ will therefore identify the difference in outcome $Y_{it}$ $\tau$ years before or after first hiring contract labor. We restrict the sample to firms (i) for which we observe an uninterrupted window spanning 3 years before and 3 years after they first hire contract workers and (ii) which hire contract workers for all 3 years following the first hire. These restrictions leave us with a sample of 715 firms. The indicator variables only turn on for plants in this sample; the rest of our sample is included to estimate the fixed effects and coefficients on the controls. We use 3 years before the date of first hire as the omitted category, so that the coefficients can be interpreted as the difference in an outcome $\tau$ years from first hiring contract workers relative to its level 3 years prior.

The results of this event study analysis are presented in Figure 8. The event studies confirm the findings from Table 3 above in that we observe a sharp rise in non-managerial employment (panel (a)), as well as sharp drops in average product (panel (b)) immediately following the hiring of contract labor. Moreover, the event studies do not suggest any evidence of pre-trends in these 3 outcomes in the years that precede the first hiring of contract labor, reinforcing our interpretation of the panel analysis above as capturing a causal effect of the use of contract labor on these firm outcomes.

5 How Did the Rise of Contract Labor Free Up Firm Growth?

We envision two main channels through which a greater reliance on contract workers may have lifted some of the labor market constraints large firms face in India. Because of the IDA, large firms face greater firing costs than smaller firms. Also, the IDA gives incumbent workers in large firms greater bargaining power than they
have in smaller firms, allowing them to bid up their wages. The contract labor system may have contributed to partially lifting these relative constraints on larger firms. We document evidence for both of these two channels below.

5.1 Reductions in Labor Adjustment Costs

As discussed above, the IDA places strict size-dependent restrictions on the ease of firing workers. These regulations bite for firms with more than 50 and 100 full-time workers, with the latter being especially costly. We think of these as an asymmetric variable adjustment cost, in the line of the Hopenhayn and Rogerson (1993) model. When productivity is mean-reverting, the firing cost introduces an inaction band into firms’ employment decisions - large firms subject to a moderate positive shock today will not hire additional workers with the knowledge that they’ll most likely have to fire them in the future. Furthermore, the firing cost could discourage firms from undertaking risky investments. Because contract workers are not counted as workmen under the IDA and are thus exempted from the application of severance pay, mandatory notice or retrenchment authorization, firms that rely more on them for their staffing needs should have smaller inaction range in their employment decisions and perhaps be more willing to undertake risky investments.

We present multiple sources of evidence consistent with this channel. Consider first the time-series around SAIL in Figure 9, panels (a) and (b). For panel (a), we first define in the firm-year data a variable called “inaction” to which we assign a value of 1 if the firm did not change its non-managerial employment by more than 10% (in absolute value) from one year to the next. We regress this inaction dummy on log employment interacted with year dummies, as well as a full set of industry and year dummies to control for compositional changes. We report in the figure coefficients on log employment for each year. The figure shows that, throughout the sample period, the likelihood of inaction increases with firm size. Most relevant to us, and consistent with a decline in relative adjustment costs at large firms post-SAIL, is the decline in the strength of this inaction to firm size relationship after 2002. Panel (b) computes the standard deviation of employment growth by firm size (less than 100 non-managerial workers; 100 to 500 non-managerial workers; more than 500 non-managerial workers) over time. Also consistent with reduced labor adjustment costs in large firms post-SAIL, we see that a sharp upward shift in the dispersion of employment growth at large firms (especially those with 500 or more non-managerial workers) starting in the early 2000s. In Appendix Figure B.5 we show that the dispersion of sales growth within large plants was stable over the period suggesting that this increased dynamics was likely driven by changes in the costs rather than benefits of adjustment.

The firm-year panel analysis in Table 3 also provides evidence of such greater employment dynamism when a given firm uses contract labor. Consider in particular rows 4, 5 and 6 in that table (even columns). We see that firms are more dynamic on the employment margin (lower likelihood of being in the inaction range; higher absolute value of employment change from one year to the next) when they rely on contract labor. Row 6 further shows evidence consistent with greater risk-taking in the product market: firms are more likely to add
new products to their output portfolio when they have contract workers on their rolls.

The remaining analysis in this section goes a step further by linking this greater employment dynamism in the presence of contract labor to greater employment sensitivity to economic shocks. We present two approaches. We first consider how districts differentially respond to local shocks based on their usage of contract labor. In particular, we construct Bartik-style instruments for growth in manufacturing employment and run regressions of the form:

$$\Delta L_{dt+k} = \beta_0 + \beta_1 \Delta L_{dt+k} + \beta_2 \text{Contract}_{dt} + \beta_3 \Delta L_{dt+k} \cdot \text{Contract}_{dt} + \gamma_s + \epsilon_{dt}$$  \hspace{1cm} (3)$$

Here $\Delta L_{dt+k} \equiv (L_{dt+k} - L_{dt})/L_{dt}$ is the growth rate of manufacturing employment in district $d$ between dates $t$ (1997-1999) and $t + k$ (2007-2009), $\text{Contract}_{dt}$ is the share of manufacturing firms using contract workers in the initial period (1997-1999), $\Delta L_{dt+k} \equiv (L_{dt+k} - L_{dt})/L_{dt}$ is the predicted growth rate in employment in the district and $\gamma_s$ are state fixed effects. \(^{16}\) To measure predicted employment growth in a district, we start by computing annual growth rates of employment at the industry level between dates $t$ and $t + k$, and then take the weighted average of these industry-specific growth rates, using initial district industry employment share as weights. We then define predicted employment in a district $\hat{L}_{dt+k}$ by multiplying initial district employment by the (gross) predicted growth rate. We exclude own-district employment when computing national industry growth rates, and standardize the contract share to have zero mean and unit standard deviation to assist interpretation. Our identification assumption is that unobserved changes in districts that affect manufacturing employment growth are uncorrelated with these changes at the national level.

Column 1 of Table 4 presents the first stage, which shows that the instrument has good predictive power for district-level employment changes. The slope is 0.783, and the F-stat is 36.41. Column 2 reports an alternative first stage that additionally controls for the vector of district level conditions in 1990 from Table 1. Again, we see that the instrument has very good predictive power.

We then examine how the initial contract share of a district (computed between 1997 and 1999) affects the responsiveness of actual employment growth to predicted employment growth. The results suggest that contract labor has a statistically and economically significant effect on responsiveness to shocks: increasing the contract share by one standard deviation raises the elasticity by about .4 (column 3) to .45 (column 4; where we also control for district level conditions in 1990). Columns 5 and 6 show that this result is robust to allowing for differential responsiveness to such economic shocks across Indian states, while column 7 shows it is robust to allowing for differential responsiveness by district characteristics (by adding interactions between predicted employment growth and district controls). In other words, the interaction term of interest is not simply picking up on differences across Indian states or types of districts in the employment responsiveness to economic shocks. Columns 8 and 9 replicate columns 5 and 6 but use district’s access to staffing employment in 1990

\(^{16}\)Unfortunately the ASI only provides district identifiers until 2009. We pool years into a pre- and post-period to increase precision.
(as computed in Section 4.2) as alternative measure of access to staffing employment. We obtain qualitatively similar results, further reinforcing our interpretation of the results in Table 4 as evidence that it is the contract labor system that is responsible for the greater responsiveness to local economic shocks, rather than some other district level characteristics that is correlated with the contract labor share. Finally, columns 10 and 11 show, as expected, that contract labor appears particularly important in increasing responsiveness to economic shocks in districts located in pro-worker states (Besley and Burgess, 2004).

Table 5 moves the analysis back to the firm-year panel and uses annual rainfall in a district as an alternative source of economic shock. In particular, the variable “shock” in this Table takes the value of 1 if rainfall in the firm’s district in that year is below the 20th percentile in that district’s average annual rainfall distribution between 1990 and 2011, -1 if rainfall in the firm’s district in that year is above the 80th percentile in the district’s distribution, and 0 otherwise.\footnote{Other researchers have provided evidence that rainfall shocks are a form of aggregate demand shocks in India. For example, Adhvaryu et. al. (2012) show that rainfall shocks (as constructed here) are associated with drops in agricultural production, wages, and district mean per capita expenditure.} The dependent variable in all regressions is log non-managerial employment. All regressions include firm fixed effects, state-year fixed effects, industry-year fixed effects and interact district level conditions in 1990 with year dummies. Standard errors are clustered at the district level.

The patterns in Table 5 are again broadly consistent with the view that the use of contract helps reduce labor adjustment costs. Column 1 shows that there is greater sensitivity to such rainfall shocks (given the coding of the shock variable, a negative coefficient is indicative of greater sensitivity) post-SAIL; however, this effect is not statistically significant. Rainfall shocks are associated with greater employment responses when firms have 25 percent of more of their workers hired under contract (column 2) and this is particularly true post-SAIL (column 3). Column 4 shows that the employment responses to rainfall shocks increase in large firms post-SAIL, e.g. in those firms that experience particularly large increase in staffing employment after the SAIL judgement. Column 5 shows greater employment responses to rainfall shocks post SAIL at firms located in districts that are closer to staffing employment in 1990. Finally, column 6 shows relatively greater sensitivity of employment to rainfall shocks after the SAIL judgement in pro-worker states.

5.2 Reductions in the Cost of Labor

A more widespread reliance on contract labor may reduce the cost of labor, and especially so for larger firms. The difference in cost between contract and permanent workers might be particularly large for firms that are subject to the IDA as these firms are more likely to be unionized, more subject to strikes and other forms of “labor militancy,” all of which may drive up the wage of their permanent workers. Also, the use of contract workers may have knock-on effects on the compensation of permanent workers themselves. In particular, by improving the outside option available to firms bargaining with unions, the contract labor system might reduce unions’ bargaining power, thereby reducing wages for their permanent workers.
We start in panel (a) of Figure 10 by plotting the elasticity of average wage with respect to total non-managerial employment over time. The average wage is defined as the total wage bill for non-managerial workers divided by the number of workers. As before, we first regress log average wage on log employment interacted with year dummies, as well as a full set of industry-year dummies to control for compositional changes and then reports in the figure coefficients on log employment for each year. There is a positive elasticity of average to employment throughout the sample period. While this positive elasticity is stable at about .13 to .14 from 1985 to 2001, the elasticity starts sharply declining starting in 2002, dropping to .08 by 2013. This time series evidence therefore shows that the SAIL event also coincided with a sharp decline in the gap in average wage between large and small firms. Panel (b) replicates panel (a) but focuses on average daily labor cost. Labor cost sums wages, bonuses, as well as various benefit payments (such as contributions to provident and other funds and other welfare expenses). Again, we see a positive and stable elasticity of daily labor cost to firm size (except for two outlier years) from 1985 to 2001 of about .19, and this elasticity starts sharply declining in 2002, reaching .12 by the end of the sample period.

The firm-year panel analysis and firm event studies above also confirm that this drop in the average cost of labor is contemporaneous with firms’ reliance on contract workers. Row 7 of Table 3 (even columns) and panel (c) of Figure 8 (event study sample) show that a firm’s average daily wage for non-managerial work goes down by 5 to 10 percent when the firm hires contract workers.

While suggestive of reduction in average cost of labor (and reduction of the firm-size gap in average cost of labor) induced by the rise of contract labor, a key limitation of the analysis above is that it is merely based on the count of the total number of workers. However, the skill composition of workforce, and hence the number of effective units of labor, may change as firms rely more and more on contract labor. In fact, because we expect contract workers to be less experienced than permanent workers, we expect the total number of units of effective labor to grow less quickly than the number of mandays when firms recruit contract labor, which would tend to exaggerate the drop in labor cost associated with the rise of the contract labor system. Ideally, we would like to estimate the difference in cost per effective unit of labor between contract and permanent workers, as well as also assess how this difference in cost varies by firm size. Unfortunately, the ASI does not contain any information on worker characteristics, making it impossible to estimate a mincerian-type wage regression to account for differences in human capital (education, experience, etc) between contract and permanent workers. Given this important limitation of the data, we proceed as follows. For each type of labor \( \ell \in \{ \text{Contract}, \text{Permanent} \} \) we run the following specification for firm \( i \) in year \( t \)

\[
\ln W_{it} = \sum_b \gamma_{ktb} \times \mathbb{I}\{\text{Contract Share}_{it} \in b\} + \beta_1 \mathbb{I}\{\ell = \text{Contract}\} + \epsilon_{it} \tag{4}
\]

where \( W_{it} \) is the average daily wage of type-\( \ell \) workers, \( \gamma_{ktb} \) are industry-year fixed affects and \( b \) are dummies.

The results are unchanged if we measure the average daily wage rather than the average wage per worker.
for categories of the share of contract workers in firm $i$ in year $t$. By controlling for the composition (e.g. share contract vs. permanent workers) of employment by industry-year cell, we hope to capture differences in the type of permanent and contract workers employed by firms with different shares of work contracted out. We allow the effect of composition to vary within each industry-year cell since the type of tasks performed by contract and full-time workers might be different across industries.

Figure 11 plots the coefficients $\beta_t$ which identify the average difference in wages between contract and full-time workers. We also repeat the analysis using total labor costs (wages, bonuses and benefits) as the outcome variable. Contract workers are about 20% cheaper than full-time workers in terms of wages, and about 25% cheaper in terms of overall payments. Of course, the finding in panel (a) does not necessarily imply that a unit of effective labor input is cheaper when sourced through contract work as we, as explained above, cannot precisely account for worker characteristics given the limitations of the ASI data. After some swings in the late 1990s and early 2000s, these wage and labor cost differences remain quite stable across the 2000s.

More relevant for our purpose is assessing whether the relative price of contract workers (compared to permanent workers) differ by firm size. In panel (a) of Figure 12 we plot the raw non-parametric relationship between the relative wage of contract workers and non-managerial employment in 2000 and 2013. Consistent with the view that the difference in the cost between permanent and contract workers is greater for large firms, we observe a downward sloping relationship. Consider the relationship in 2000: in firms with 10 non-managerial workers, contractors are paid about 10% ($\exp(0.1) - 1 \times 100$) less than full-time staff, but this difference increases to 22% (47%) in firms with 100 (1000) non-managerial workers. In panel (b) we residualize the relative wage by industry-year-contract labor share bin fixed effects as before, and we observe the same qualitative pattern. The downward slope is particularly steep in 2000 for plants above the 100 permanent workers mark. This downward slope is consistent with the additional bargaining power we hypothesize permanent workers to have in larger firms under the IDA, and one of the reasons why the rise in contract labor may have reduce the gap in labor cost between larger and smaller firms. Of course, as stated many times before, we cannot rule out that differences in workers’ human capital in large vs small firms are also in part responsible for this gradient.

Furthermore, we also observe that this relationship flattens in 2013 compared to 2000 for plants with more than 100 full-time workers, yet is almost identical for smaller establishments. In other words, the relative cost of contract workers increased disproportionately over the 2000s for large firms. In panel (c) we explore the timing of this change by augmenting the specification (4) as follows:

$$\ln W_{it} = \sum_{b} \gamma_{kth} \times \mathbb{I}\{\text{Contract Share}_{it} \in b\} + \beta_1 \mathbb{I}\{\ell = \text{Contract}\} + \beta_2 \ln L_{it} + \beta_{t} \times \mathbb{I}\{\ell = \text{Contract}\} \times \ln L_{it} + \epsilon_{it}$$

In particular, we allow for 5 contract labor share categories corresponding to whether the firm employs no contract workers, between 0-24%, 25-49%, 50-74%, or 75-100% of workers through contracting.

The years plotted correspond to those for which wages and bonuses/benefits are provided separately for full-time and contract workers in the ASI.
where $L_{it}$ is the number of non-managerial workers. The coefficients $\beta_{Size}^{t}$ therefore capture the extent to which the wage differential between contract and full-time workers vary with the number of workers employed at the establishment. Panel (c) of Figure 12 plots these coefficients. While our data only allow us to examine this relationship from 1998 onwards, it appears the fall in the wage premia of full-time workers within large plants began around or just after the SAIL adjudication.

Figure 12 suggests that the cost of full-time workers relative to contractors is falling for larger plants during the 2000s. In Figure 13, we diagnose whether this was driven by an increase in contract wages or a fall in full-time wages at larger firms during the 2000s. Panel (a) plots the elasticity over time of the average wage per contract worker to the number of non-managerial workers (constructed in the same way as the previous elasticity plots). There is a positive elasticity of around 0.05 over the period, suggesting that larger plants faced higher wages to hire contract workers. This rises and then falls slightly around the SAIL event, but the magnitude of the change is relatively small.

Panel (b) repeats this analysis but focuses on changes over time in the elasticity of the elasticity of the average wage of permanent workers to the number of non-managerial workers. Here, we observe a very pronounced drop post-SAIL. Full-time workers became disproportionately cheaper for large firms starting from the 2001. While our wage data by worker category only begin in 1998, the lack of a pre-trend in the non-managerial wage elasticity in Figure 11 suggests the full-time wage elasticity was likely constant prior to 1998 given the dominance of full-time vis-a-vis contract workers during those early years.

Overall, panels (a) and (b) of Figure 13 suggest that the rise in the relative cost of contract workers amongst large plants documented in Figure 12 was driven by a fall in the cost of full-time workers rather than a rise in the cost of contract workers. Panel (b) suggests that this changes lines up fairly closely with the SAIL decision. To provide further evidence, panel (c) examines how the relationship between the elasticity of full-time wages to non-managerial employment and a district’s level of staffing in 1990 evolved over time. If the SAIL decision was the principal factor driving the downward trend in this elasticity during the 2000s, then we expect that districts with more staffing available (in 1990) should experience a larger decline after 2001. To test this, we regress log full time wage per worker on a full interaction of log non-managerial employment, log 1990 staffing and year dummies, as well as a set of district, industry-year-contract labor share bin and state-year fixed effects and 1990 district characteristics interacted with year fixed effects. The triple interaction term in this difference-in-difference-in-difference regression captures the change in the full-time wage plant size elasticity in a given year for a 1% increase in the 1990 staffing measure, relative to the omitted category (1998), compared to other districts in the same state with the same baseline characteristics. If these coefficients are negative, then the wage-plant size elasticity for full-time workers fell more in districts with greater exposure to staffing in 1990. Panel (c) shows the results. While noisy, there is a clear downward trend in these coefficients post-2001. Overall, these results support the hypothesis that by reducing the bargaining power of full-time workers, the proliferation of contract labor had an additional and indirect impact on labor costs for large manufacturing plants.
Before concluding this section, we note that there are other mechanisms via which the rise in contract labor may have affected labor cost. Another channel through which contract labor may decrease the cost of a unit of effective labor input is because staffing firms can exploit economies of scale in HR and administrative services that allow manufacturers to reduce overall labor costs under the outsourcing arrangement. The staffing companies may also provide services in handling a complex web of state labor laws. The story of Whirlpool’s entry in the India, as reported in the New York Times in 2011, provide a good example: “In 1997, a few years after Whirlpool arrived in India, it hired hundreds of salesmen and sent them to independent retail stores to sell washing machines, refrigerators and air-conditioners to middle-class Indians who had never bought such appliances before. But soon executives were overwhelmed trying to keep abreast of changes in labor laws and various minimum-wage rules in India’s 28 states. So Whirlpool began outsourcing its sales staff, which has since grown to 1,850 people — first to a staffing agency called Adecco and later to TeamLease. Excluding 250 people who work at the company’s own stores, most of its sales workers are employed by TeamLease, which handles their wages, commissions, health care and retirement savings.”\textsuperscript{21} While we cannot directly test for this channel given the data limitation, we note that one would expect smaller firms to disproportionately benefit here as larger firms are more likely to already have their own internal recruiting, HR and payroll departments. In other words, given the patterns documented above of a rise in the reliance on contract labor concentrated in larger firms, it seems unlikely that this particular channel is the main one via which the rise in contract labor changed the formal Indian manufacturing sector.

Also, staffing firms may reduce the search and matching frictions that manufacturing firms face in the labor markets. It allows firms to experiment with potential long-term employees. Firms may employ a worker on a short-term contract to learn about the productivity of a potential match before deciding on whether to take on a worker full-time. Staffing firms may also help in this regard if their labor pooling allows them to better match employees to employers. While we do not rule out the possibility that the staffing industry is playing this role, it does not seem to be the sole explanation for the patterns documented above. Both large and small firms should benefit from better matching. Assuming this channel, the fact that the rise in contract labor is concentrated in larger firms suggest that labor regulations may have made it particularly costly for larger firms to experiment with potential long-term employees.

Finally, another mechanism through which contract labor may reduce the cost of a unit of effective labor input is through benefit avoidance. Larger firms may face stricter monitoring by regulators, and hence be less able to avoid paying the suite of mandated benefits to their permanent workforce. It might be easier for larger firms to avoid paying those benefits to the workforce that is contracted out. Panel (a) in Figure 14 shows how the fraction of firms of a given size paying zero benefits to all workers evolved over time.\textsuperscript{22} While large firms

\textsuperscript{22}Note this includes non-managerial and managerial workers since only aggregated benefits are provided across both decades in the ASI. Panel (b) shows the stability of the relationship between benefits and plant size during the 2000s is echoed in the relationship between the ratio of benefit to wages for full-time non-managerial workers and the number of these workers employed within
are always more likely to pay benefits, we see that the main period of increased enforcement was during the 1990s. The schedules in 2000 and 2013 are almost identical. Panel (b) examines how the elasticity between the cost share of benefits paid to full-time workers (defined as benefits divided by the wage bill) and full-time employment changed over time. The relationship was remarkably constant over the period, suggesting the increase in contract labor use during the 2000s was not likely due to increased enforcement of benefits paid to permanent workers.

6 A Model of Firm Growth and Innovation subject to Firing Costs

In this section, we develop a model of firm dynamics to take to the data in order to quantify the effect of contract labor on TFP growth in Indian manufacturing. We model the IDA as imposing firing costs on large firms. We think of the spread of contract workers as reducing the bite of these adjustment costs, and estimate the size of this reduction using moments informed by the reduced form effects previously documented. While we focus on the most immediate benefit that contract labor provides by reducing firing costs, we will see that this single channel is able to capture most of the patterns observed in the data. In particular, the anticipation of future retrenchment causes large firms to hire a suboptimally low number of workers (increasing the average product of labor) and to invest less in innovation (reducing the likelihood they grow by adding a new product). In this way, firing costs reduce the level and growth rate of aggregate productivity.

6.1 Consumers

The economy is in continuous time and has a representative household with log utility given by

\[ U = \int_0^\infty e^{-\rho t} \ln C_t dt. \tag{5} \]

where \( C_t \) is a CES aggregator over a fixed unit continuum of goods available in the economy. The representative household can save in asset markets at rate \( r_t \), and has a measure \( L_\ell \) of unskilled labor and \( L_h \) of skilled labor supplied inelastically, receiving wages \( w_\ell^t \) and \( w_h^t \) respectively. The budget constraint is then given by

\[ \dot{A}_t + C_t \leq r_t A_t + w_\ell^t L_\ell + w_h^t L_h \tag{6} \]

Along a balanced growth path, the Euler equation implies \( g = r - \rho \). Since the economy is closed and all factor payments by firms accrue to labor, output is equal to consumption \( Y_t = C_t \).
6.2 Firms

Setup

Each product $j \in [0, 1]$ is produced by the monopolist who owns the best leading edge technology for the product, and firms can own multiple products and produce multiple goods simultaneously.\footnote{As in Akcigit and Kerr (2015), we assume firms pay a small fixed cost $\epsilon > 0$ to enter a bidding game to produce each variety, so that in equilibrium only the holders of the leading technology ever produce. Firms therefore act as monopolists over their own varieties.}

A firm $f$ is characterized by a collection of products $J_f$ with productivities $Q_f = \{q_j : j \in J_f\}$. CES demand for each product is given by $y_{jt} = p_j^{\sigma} P_i^{\sigma-1} Y_t$. Firms produce using a linear technology $y_{jt} = q_j \ell_{jt}$ that depends on productivity and the number of low-skill workers $\ell_{jt}$ whose wage is $w^t_f$.

Firms also engage in innovation activities. When a firm with $n$ products hires $h$ high-skill workers at wage $w^h_t$ to work on innovation, it adds a new product to its portfolio at the flow rate $X = \theta n^\beta h^{1-\beta}$. It therefore costs a firm with $n$ products $c(x, n) = w^h_t nx^{1/\gamma} \theta^{-1/\gamma}$ to produce innovation at a rate $x \equiv X/n$ per product. When a firm successfully innovates over a (random) product with productivity $q$, it increases the productivity by proportion $1 + \lambda$ so that $q' = (1 + \lambda)q$.

We assume that firms differ in their innovative capacities. In particular, on entry firms draw a type $\theta \in \{\theta_L, \theta_H\}$ where $\theta_L$ are less innovation low-type firms and $\theta_H$ are high-type with $\theta_H > \theta_L \geq 0$. Firms draw types from a Bernoulli distribution with

$$P(\theta = \theta_H) = \alpha \quad \text{and} \quad P(\theta = \theta_L) = 1 - \alpha.$$ 

A pool of entrants also engages in innovative activities. At rate $x_e$ they innovate over a random product, again increasing its productivity by proportion $1 + \lambda$.

In order to match the content of the IDA, we assume that firms are subject to variable firing costs that depend on the number of workers retrenched. Here we make two simplifying assumptions. First, we assume that costs are only paid when firms lose a product to a successful innovation by a competitor. This fits the institutional context in India where imperfect enforcement of the IDA means it is likely to bite for more significant retrenchments.\footnote{Consistent with this, we do observe many cases of reductions in full-time workers across all firms in the ASI, although we recognize part of this may be due to measurement error.} Second, we assume that adjustment costs are specific to a firm’s type rather than the level of employment within the firm. Without this assumption, we would quickly run into a curse of dimensionality that renders numerical solutions to the model infeasible.\footnote{A firm’s value function will depend on the productivity of each of its products (an $n$-dimensional object). Since the number of products a firm can own is unbounded, we seek a framework in which the value of a firm can be written as the sum of the value of holding each of its products (a one-dimensional object). This is the approach taken by others in the literature (e.g. Acemoglu et. al. 2013, Akcigit and Kerr 2015). If adjustment costs depend on the total employment or number of products in the firm, then activities in one product line (such as hiring decisions or adding/losing that product) change the state variable for all others, removing this separability across product lines and rendering the value function $n$-dimensional once more. Note this only applies to the case of $\sigma \neq 1$; in the case of Cobb-Douglas preferences then we can accommodate these alternatives, but then marginal revenue products are equalized across firms since the sales share of each product is identical.} However, our model still captures the size-dependent na-
ture of the IDA well. In particular, we will assume that high-type firms who are more productive at innovating and thus more likely to grow large are subject to higher adjustment costs. In equilibrium, large firms will be subject to higher adjustment costs.

Value Functions

Along a BGP all growing variables evolve at the same rate. Define the value of a type-\( k \) firm of holding products with productivities \( Q \) as \( V_{k,t}(Q) = V_k(Q) Y_t \) where \( V_k \) is the normalized value function. Let \( \tau \) denote the average creative destruction rate that reflects the probability a firm loses a product to a competitor in any instance; this will be determined in equilibrium. As we show in the appendix, the normalized value function is given by

\[
\rho V_k(Q) = \max_{x,\{\ell_j\}} \left\{ \sum_j \left[ \left( q_j \ell_j P\right)^{\frac{\sigma-1}{\sigma}} - \omega_t \ell_j - \omega_h x^{\frac{1}{1-\beta}} \theta_k^{\frac{1}{1-\beta}} \right] + \tau \left[ V_k(Q \setminus \{q_j\}) - \kappa_k x \ell_j - V_k(Q) \right] + x \left[ E_q \left[ V_k(Q \cup q) - V_k(Q) \right] \right] \right\}
\]

(7)

where \( \omega_t \equiv w^t_t / Y_t \), \( \omega_h \equiv w^h_t / Y_t \) and \( P \equiv P_t / Y_t \) are constants along a BGP.

The value function in (7) can be interpreted as follows. The firm chooses the innovation rate and employment per product in order to maximize its value. The first line reflects static profits from these choices. This is determined by firm sales net of payments to low-skilled workers engaged in production as well as high-skill workers engaged in innovation. The next two lines reflect the probability the firm moves to another state in the next instance. The second line expresses the change in value if the firm loses one of its products through creative destruction. If the firm loses product \( j \) it enters state \( Q \setminus \{q_j\} \) and exits \( Q \). However, when a firm loses a product they also pay the variable firing cost \( \kappa_k x \ell_j \). Our assumption that high-type firms face larger adjustment costs implies \( \kappa_H > \kappa_L \geq 0 \). The third line reflects the change in value if the firm successfully innovates over a product, which they draw at random from competitors.

Employment Decisions

To characterize firm behavior, we begin by considering the employment problem of the firm. This problem is separable across all products the firm owns and for any product \( h \) reduces to

\[
\max_{\ell_j} \left\{ \left( q_j \ell_j P\right)^{\frac{\sigma-1}{\sigma}} - \ell_j \omega_t (1 + \tau \theta_k) \right\}
\]

The solution implies

\[
\ell_k(q) \propto (1 + \tau \theta_k)^{-\sigma} q^{\sigma-1}
\]

(8)
Substituting this back provides a simple expression for flow profits as

\[ \pi_k(q) = A_k q^{\sigma - 1} \]

where \( A_k \equiv \frac{1}{\sigma} \left( \frac{\sigma}{\rho - \tau} - \frac{\omega_0(1 + \tau \kappa_k)}{\rho} \right)^{1 - \sigma} \).

Equation (8) provides intuition for the way in which firing costs distort employment decisions in the model. Notice that in the absence of adjustment costs \( \ln \ell_k(q) - \ln e_k^{\text{opt}}(q) = -\sigma \ln (1 + \tau \kappa_k) \). In words, firms subject to higher adjustment costs employ less workers than in the undistorted optimum. The reason is that when firms hire workers to produce a product in any period, they anticipate losing that product with probability \( \tau \) in which case they have to pay \( \omega_k \) in firing costs. This leads the cost to hiring those workers to rise above their wage, increasing these firms marginal revenue product of labor. This in turn reduces flow profits from holding these products, since they face this additional labor wedge.

These insights allow us to substantially simplify the firm value function, as the following lemma establishes.

**Lemma 1.** The value function of a firm can be written as the sum of the value of its products \( V_k(Q) = \sum_j v_k(q_j) \), where the value of holding a product with productivity \( q \) is given by

\[ v_k(q) = A_k q^{\sigma - 1} + B_k \tag{9} \]

where

\[ A_k = \frac{\pi_k}{\rho + \tau} \quad \text{and} \quad (\rho + \tau)B_k = \beta \theta_k^{\frac{1}{\beta}} \left( \frac{A_k E [q^{\sigma - 1}] + B_k}{\omega_h^{1 - \beta}} \right)^{\frac{1}{\beta}} \]

Defining \( \tilde{\beta} \equiv (1 - \beta) \frac{1 - \beta}{\beta} \), optimal innovation per product is given by

\[ x_k = \tilde{\beta} \theta_k^{\frac{1}{\beta}} \times \left( \frac{A_k E [q^{\sigma - 1}] + B_k}{\omega_h} \right)^{\frac{1 - \beta}{\beta}} \tag{10} \]

The value function has an additive form where the value of the firm can be written as the sum of the value of each of its products. This value has a simple analytical form that depends on the productivity of the product as well as the type-specific constants \( A_k \) and \( B_k \). The value of holding a product with productivity \( q \) differs across firm types due to adjustment costs. In particular, notice that \( A_L > A_H \) since \( \kappa_H > \kappa_L \) implies that \( \pi_L > \pi_H \). \( B_k \) also depends on \( \kappa \) implicitly through \( A_k \); while the derivative of this with respect to \( \kappa \) can depend on model parameters, we assume that parameters are such that the expected value of gaining a new product \( A_k E [q^{\sigma - 1}] + B_k \) is decreasing in \( \kappa \). This is intuitive since these firms face lower flows profits.\(^{26}\) We

\(^{26}\)For this to be the case we require that \( A_k E [q^{\sigma - 1}] + B_k \) is increasing in \( A_k \). Implicitly differentiating the expression for \( B_k \), this turns out to hold if \( \rho + \tau - \frac{A_k}{\beta \omega_h} > 0 \).
also assume that the differences in $\theta_k$ are large enough so that $x_H > x_L$ even in the presence of adjustment costs. This will ensure that more productive high-type firms grow larger, but are constrained by higher adjustment costs.

**Entrants**

A unit mass of potential entrants have access to the same innovation technology as incumbents: they produce flow rate of innovation $x_e$ at cost $u_h x_e^{1-\beta} \theta_{E}^{1-\beta}$. If they successfully innovate over a product, they become a high type with probability $\alpha$ and otherwise become a low type. Their maximization problem is simply

$$\max_{x_e \geq 0} \left\{ x_e \left( \alpha E [v_H(q)] + (1 - \alpha) E [v_L(q)] \right) - \omega_h x_e^{1-\beta} \theta_{E}^{1-\beta} \right\}.$$ 

The solution implies that

$$x_e = \beta \theta_{E}^{1-\beta} \left( \frac{\tilde{A} E [q^{\sigma-1}] + \tilde{B} }{\omega h} \right)^{1-\beta},$$

where $\tilde{A} \equiv \alpha A_H + (1 - \alpha) A_L$ and $\tilde{B} \equiv \alpha B_H + (1 - \alpha) B_L$.

### 6.3 Aggregation

**Labor Market Clearing**

**Low-Skill Workers** Labor market clearing for low-skill workers requires $L_u = \int \ell_j dj$. To right this in a more intuitive form, we begin by rewriting employment as a function of firm sales as

$$\ell_j(q_j) = \frac{\sigma-1}{\sigma} \frac{p_j g_j(q_j)}{\omega_f(1+\tau \kappa_j)}$$

where $\kappa_j$ is the adjustment cost faced by the producer of $j$. The labor market clearing condition can then be written as

$$L_u = \frac{\sigma-1}{\sigma} \frac{P}{MRPL}$$

where

$$\frac{1}{MRPL} \equiv \int \frac{1}{\omega_f(1+\tau \kappa_j)} \gamma_j dj$$

where the revenue share of product $j$ $\gamma_j = \frac{p_j y_j}{P Y_t} = \frac{\sigma \pi_j q_j^{\sigma-1}}{P}$ is constant along a BGP. In combination with the expression for the price index, we find that

$$Y = AL_u$$

where $A = \left[ \int \left( q_j \frac{MRPL}{MRPL_j} \right)^{\sigma-1} dj \right]^{\frac{1}{\sigma-1}}$

where we have defined the marginal revenue product of labor for product $j$ as $MRPL_j \equiv \omega_f(1+\tau \kappa_j)$. 

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As in Hsieh and Klenow (2009), the economy operates as if there is a representative firm with productivity $A$ determined by a generalized mean of firm-specific (weighted) productivities. In the undistorted economy, $MRP_{L_j}$ is constant across firms and thus $A^{opt} = \left[ \int q_j^{\alpha - 1} d_j \right]^{\frac{1}{\alpha - 1}}$. By introducing differences in labor wedges across firms, adjustment costs lead aggregate productivity to deviate from its frictionless optimum.

**High-Skill Workers** Labor employed in innovation by entrants and incumbents are $h^e = (x_e/\theta_E)^{\frac{1}{\beta}}$ and $h_{k(j)} = (x_{k(j)}/\theta_{k(j)})^{\frac{1}{1-\beta}}$ respectively. Together, labor market for skilled workers therefore requires that

$$L_s = \left( \frac{x^e}{\theta_E} \right)^{\frac{1}{1-\beta}} \sum_k \mu_k \left( \frac{x_k}{\theta_k} \right)^{\frac{1}{1-\beta}} \quad (13)$$

**Steady State Distributions**

We now solve for the distribution of productivity $F$ as well as the shares of firm types $\mu_k$.

**Firm Types** To solve for the steady state distribution of firms of type $k$, we need to equate the inflows with the outflows from each distribution. Consider high-type firms. Inflows are entrants who become high-type and innovate over a low-type product, as well as incumbent high-type firms who do the same. Outflows are entrants who become low-type firms and innovate over high-type products, as well as low-type incumbents who do the same. The same applies for low-type firms. Equating these two flows implies that

$$x^e (\mu_H - \alpha) = (x_H - x_L) \mu_H (1 - \mu_H) \quad (14)$$

$$\mu_L = 1 - \mu_H \quad (15)$$

Notice that since $x_H > x_L$ this implies $\mu_H > \alpha$ so that in equilibrium there are more products produced by high-type firms than the number of these firms that enter. This reflects the product stealing that arises from their greater innovation intensities.

**Stationary Productivity Distribution** Once again, we solve for the stationary productivity distribution for firms of each type by equating inflows with outflows from each part of the distribution. Consider the inflows to $f_H(q)$. There are $\alpha x^e$ entrants who enter this state by stealing from either high- or low-type firms at $\frac{q}{1+\lambda}$. The same applies to incumbent high-type innovators of which there are $\mu_H x_H$ in total. The outflows are simply the mass of incumbents $\mu_H f_H(q)$ who lose their product with probability $\tau$. Similar logic applies to the movements in and out of $f_L(q)$. Equating these flows yields

$$(\alpha x^e + \mu_H x_H) \left( \mu_H f_H \left( \frac{q}{1+\lambda} \right) + (1 - \mu_H) f_L \left( \frac{q}{1+\lambda} \right) \right) = \tau \mu_H f_H(q) \quad (16)$$

$$(1 - \alpha) x^e + \mu_L x_L \left( \mu_H f_H \left( \frac{q}{1+\lambda} \right) + (1 - \mu_H) f_L \left( \frac{q}{1+\lambda} \right) \right) = \tau \mu_L f_L(q) \quad (17)$$

Together, this provides a system of 2 functional equations in $f_H, f_L$. 

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6.4 Growth

The aggregate rate of innovation is determined by successful innovations by the three types of firms in the economy by

$$\tau = \sum_k \mu_k x_k + x_e$$

The following lemma provides an expression for the growth rate of aggregate variables along a BGP. From (12), this is simply the growth rate of TFP $g = \frac{\dot{A}}{A}$.

**Lemma 2.** The growth rate of the economy is equal to

$$g = (1 + \lambda)^{\sigma-1} \left[ x^e \bar{\vartheta} + \sum_k \mu_k x_k \vartheta_k \right] - \tau$$

where $\vartheta_k = \frac{1}{A} \int_0^1 \left( q_j \frac{MRPL}{MRPL_k} \right)^{\sigma-1} dj$ and $\bar{\vartheta} = \alpha \vartheta_H + (1 - \alpha) \vartheta_L$.

Notice that the constants $\vartheta_k$ are the ratio of steady state TFP if all firms were type-$k$ to actual TFP. Since $MRPL_L < MRPL_H$ we have $\vartheta_H < 1$ and $\vartheta_L > 1$, so adjustment costs inflate the contribution of less innovative low-type firms to aggregate growth.

When distortions are equalized so that $\vartheta_L = \vartheta_H = 1$. Using the definition of $\tau$ above (evaluated at the levels of innovation in the undistorted economy) the growth rate simplifies to

$$g^{opt} = \frac{\tau^{opt}((1 + \lambda)^{\sigma-1} - 1)}{\sigma - 1}$$

6.5 Welfare

Since $C_t = Ce^{gt}$ along a BGP, we can use $C = Y = AL_u$ to show that welfare $U = \int_0^\infty e^{-\rho t} \ln C_t dt$ is given by

$$U = \frac{1}{\rho} \left[ \ln A + g \right]$$

To build intuition, assume that $q_j, MRPL_j$ are drawn iid from log-normal distributions. In this case, we have that

$$U^{opt} - U \propto \frac{\sigma}{2} \Var \ln MRPL_j + \frac{g^{opt} - g}{\rho}$$

where $U^{opt} = \frac{1}{\rho} \left[ \frac{1}{\sigma - 1} \ln E \left[ q^{\sigma-1} \right] + \frac{g^{opt}}{\rho} \right]$ is welfare in the undistorted economy.

The distortions $MRPL_j$ introduced across firms by the size-dependent firing costs therefore have two effects. First, they introduce a static misallocation which decreases the normalized TFP $A$. Only the dispersion of these distortions matters. Second, they distort the innovation incentives of both entrants and incumbents which causes the growth rate to deviate from the undistorted optimum.
6.6 Equilibrium

**Definition.** Given parameters \( \{\rho, \alpha, \beta, \kappa, \theta_k, \theta_E, \lambda, \sigma, L_s, L_u\} \), a BGP equilibrium in this economy is defined by the tuple

\[
\{\ell_j, p_j, y_j, \omega_u, \omega_s, v_k(q), x_k, x_e, f_k(q), \mu_k, g, r\}
\]

such that (i) optimal employment is given by (sub8), (ii) \( y_j = q_j \ell_j \) and \( p_j \) is the CES markup over marginal cost, (iii) \( \omega_u \) and \( \omega_s \) solve the labor market clearing conditions (13) and (12), (iv) the value function is given by (9), (v) innovation by incumbents and entrants are given by (10) and (11), (vi) the steady state distributions across productivities and firm types are given by (16) and (17) and (14) and (15), (vii) the growth rate \( g \) is given by (18) and (viii) the interest rate is consistent with the Euler equation so that \( g = r - \rho \).

7 Estimation and Quantification

These results are forthcoming.

8 Conclusion

We provide evidence that the employment restrictions on large Indian firms appears to have diminished since the late 1990s. We argue that this is driven by the expansion of formal staffing companies that provide contract workers primarily to large firms, itself spurred by a legal change that reduced the costs to firms of hiring contractors. The use of contract labor allows large Indian firms to respond to shocks to profitability, expand employment, and invest in new products. In the data, this shows up as an increase in the thickness of the right tail of the firm size distribution in India, a decrease in the average product of labor of large Indian firms, and an increase in the dispersion of employment growth. However, it is clear that the use of contract labor is only a partial solution to the problem. Despite the improvements seen in the data since the late 1990s, it is still the case that average product of labor in large Indian firms is substantially higher than that of smaller firms, the dispersion of employment growth is still significantly lower than in the US, and that Indian manufacturing is still dominated by a large number of small informal establishments.
References


### Tables

#### Table 1: 1990 Staffing and the Growth of Contract Labor Use in Manufacturing Plants

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Note: Observation is a firm-year. Outcome is a dummy for whether the firm hires more than 0, 25 or 50 percent of non-managerial workers through contract labor. Post is a dummy for after 2001. Staffing is the weighted staffing employment in 1990 in all other districts with a decay rate of 0.0075. Controls include log average formal manufacturing firm size, log district total employment, manufacturing share of all district employment, manufacturing share of district formal employment, share of establishments younger than 5 years in the district, all measured in 1990. Standard errors clustered at the district level reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

#### Table 2: Heterogeneous Outcome Growth Post-SAIL by 1990 Staffing

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Note: Observation is a firm-year. Each entry corresponds to the coefficient from a regression of the outcome in each row on the log staffing measure interacted with a Post-SAIL dummy. Each column corresponds to a specification. Wght Emp refers to weighted total employment in 1990 constructed in the same way as the staffing measure. Dist controls include dummies for plant ownership and organization type as well as a polynomial in firm age, interacted with a post-SAIL dummy. District controls include log district total employment, average formal manufacturing firm size, manufacturing share of district total and formal employment, share of firms younger than 5 in district, all measured in 1990 and interacted with a Post-SAIL dummy. Standard errors clustered at the district level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.
### Table 5: Contract Labor and Responsiveness to Rainfall Shocks

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Note: Observations at the firm-year level. Outcome is log non-managerial employment. Post is a dummy for after 2001. Shock is defined at the district level and defined by relative rainfall in a year relative to the average. It takes a value of 1 when rainfall is below the 20th percentile of a district’s distribution, -1 when above the 80th percentile and 0 otherwise. Contract is a dummy for whether the firm hires more than 25% of workers through contract labor. Large is a dummy for whether the firm has more than 100 workers. Staffing is the weighted staffing employment in 1990 in all other districts with a decay rate of 0.0075. Pro-worker states are defined by the Besley-Burgess measure. District conditions include (all measured in 1990) the difference in logAPL between firms with more and less than 50 workers, log average manufacturing firm employment, the share of young firms less than 5 years old, log district total employment, the manufacturing share of district employment and the manufacturing share of formal employment. Standard errors clustered at the district level.* p < 0.1; ** p < 0.05; *** p < 0.01.
Table 3: Heterogeneous Outcome Growth Post-SAIL by 1990 Staffing

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<td>0.433***</td>
<td>0.350***</td>
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<td>(0.018)</td>
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<td>0.166***</td>
<td>-0.132***</td>
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<td>(0.012)</td>
<td>(0.007)</td>
<td>(0.013)</td>
<td>(0.008)</td>
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<td><strong>logAPL</strong></td>
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<td>-0.191***</td>
<td>0.354***</td>
<td>-0.201***</td>
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<td>(0.022)</td>
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<td>(0.020)</td>
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<td>-0.016***</td>
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<td>-0.030***</td>
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<td></td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.007)</td>
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<tr>
<td><strong>Abs g</strong></td>
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<td>0.007</td>
<td>0.021***</td>
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<tr>
<td><strong>Add Output Product</strong></td>
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<td>0.003</td>
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<td><strong>logAvgWage</strong></td>
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<td>0.116***</td>
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<td>Industry-Year FE</td>
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<td>Firm FE</td>
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<td>X</td>
<td>X</td>
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</tbody>
</table>

Note: Odd columns report the coefficient from a regression of the outcome on a dummy for whether or not the firm ever hires more than a certain fraction of workers through contracting. All firms that never hire contract labor are included, and only observations from firms that ever hire contract labor in years before the first year they hire contract labor are included. Even columns report the coefficient from a regression of the outcome on a dummy for whether or not the firm hires more than a certain fraction of workers through contracting in a given year. Only firms who ever hire more than a certain fraction of workers through contracting are included. Data covers 1993-2013. Standard errors clustered at the district level.* p < 0.1; ** p < 0.05; *** p < 0.01
Table 4: Contract Labor and Responsiveness to Local Shocks

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<td>0.842***</td>
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<td>0.982***</td>
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<td>(0.130)</td>
<td>(0.150)</td>
<td>(0.121)</td>
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<td>0.628**</td>
<td>0.622***</td>
<td>0.639***</td>
<td>0.655***</td>
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<td>0.440*</td>
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<td>Pro-Worker State X Initial Contract Measure</td>
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<td>0.962*</td>
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<td>X Pro-Worker State X Initial Contract Measure</td>
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Note: Observations at the district level. The outcome in each column is the growth in district ASI employment between 1997-1999 and 2007-2009. Predicted Emp Growth is the predicted employment growth rate according to the Bartik measure using the aggregate rate of employment growth across industries in all other districts as defined in the text. Pro-worker states are defined by the Besley-Burgess measure. Initial contract measure is the share of firms using contract labor in the district between 1997-1999, standardized to have unit standard deviation (except in columns (8) and (9) where it is the log staffing measure, also standardized). Specifications include all districts and are weighted by the district’s average number of observations across both pre- and post-periods. Controls include, in 1990, total district employment, manufacturing share of employment, manufacturing share of total employment, urban share of manufacturing employment, average firm size, share of young firms (less than 5 years of age). Standard errors clustered by district reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$
Figures

Figure 1: Firm Size Distribution: 2000 vs 2013

Note:
Figure 2: APL and Firm Size: 2000 vs 2013

Note: Plot contains results from non-parametric regression of log APL on log Employment using Epanechnikov kernel with a bandwidth of 0.6, where employment in both variables is the number of non-managerial workers. LogAPL is residualized by industry and year fixed effects before running the regression.

Figure 3: Employment Growth Dispersion and Firm Size: 2000 vs 2013

Note: For each bin of non-managerial employment, plot shows the standard deviation of annual non-managerial employment growth within plants in 2000 and 2013.
Figure 4: Contract Labor Use and Firm Size: 2000 vs 2013

(a) Any Contract

(b) Contract>50% Employment

Note: Plot contains results from non-parametric regression of the probability a plant hires more than a certain fraction of non-managerial workers through contractors on (log) non-managerial employment. In panel (a) the contract measure is a dummy equal to one if the plant hires any contract workers while in panel (b) the measure equals one if it hires more than 50% through contractors.
Figure 5: SAIL and Contract Labor Use by Firm Size

(a) Any Contract

(b) Contract>50% Employment

(c) Contract>50% Employment, Pro-Worker States

(d) Contract>50% Employment, Pro-Employer States

Note: Plot shows coefficients on size by year interactions from a regression of a dummy for whether a plant hires more than a certain fraction of non-managerial workers through contractors on year, industry, and size by year interactions. Size is defined by non-managerial employment bins of 0-100, 100-500 and 500+ workers (0-100 are the omitted category). Panels (a), (b) and (c) construct the contract use dummies for whether a plant hires more than 0, 50 or 75% of workers through contractors respectively. Panels (d) and (e) run the specifications seperately in states which are por-worker and pro-employer according to the Besley and Burgess (2004) measures. 95% confidence intervals plotted with robust se’s.
Figure 6: Firm Size Percentiles Over Time

Note: Plot shows percentiles of non-managerial employment in the ASI indexed to their values in 1985.

Figure 7: Average Products of Labor and Capital and Plant Size Over Time

(a) APL-Plant Size Elasticity

(b) APK-Plant Size Elasticity

Note: Plot shows coefficients from regressions of log APL (panel (a)) and logAPK (panel (b)) on log plant size (measured by non-managerial workers) interacted with year fixed effects. Regressions also include full set of year and industry fixed effects. 95% confidence intervals plotted with robust ses.
Figure 8: Event Studies Around First Year of Hiring Contract Labor

(a) Non-Managerial Employment

(b) APL

(c) Average Wage

Event study sample includes 715 firms which we observe 7 uninterrupted years, with 3 years before CL uptake and 3 years after, and contract labor hired in all years after initial hire. Regressions sample includes 60278 firms.

Note: Plots report coefficients on year from hiring contract labor dummies on each outcome, as well and industry-year and state-year fixed effects and a 4th order polynomial in plant age. Full sample is included, but year from hiring dummies on vary for establishments in our sample of 715 plants for which we observe 7 uninterrupted years, with 3 years before contract labor first hire and 3 years after, with contract workers hired in all years after the initial hire. 95% confidence intervals plotted with robust ses.
Figure 9: SAIL and Employment Dynamics

(a) Inaction-Plant Size Elasticity

(b) Employment Growth Dispersion

Note: Panel (a) plot shows coefficients from regressions of a dummy for whether a plant’s annual employment growth rate exceeds 0.1 in absolute value on log plant size (measured by non-managerial workers) interacted with year fixed effects. Regressions also include full set of year and industry fixed effects. 95% confidence intervals plotted with robust ses. Panel (b) shows the standard deviation of non-managerial employment growth in each year relative to 1994. Employment growth is detrended by industry and year fixed effects before collapsing. Size bins defined according to non-managerial employment.

Figure 10: Labor Cost and Plant Size Over Time

(a) Wage-Plant Size Elasticity

(b) Labor Cost-Plant Size Elasticity

Note: Figures plot coefficients from regression of log wage per non-managerial worker (panel (a)) and log labor cost per non-managerial worker (defined as wages, bonuses and benefits, panel (b)) on log non-managerial employment interacted with year fixed effects. Regressions also include full set of year-industry fixed effects. 95% confidence intervals plotted with robust ses.
Figure 11: Relative Cost of Contract Labor

Note: Figures plot coefficients from regression of log wage per worker on a dummy for whether the worker category is contract (relative to the omitted category of full-time workers) interacted with year fixed effects, as well as a full set of industry-year-contract labor share bin fixed effects, where contract labor share bins are dummies for whether the plant hires no contract workers, between 0-24%, 25-49%, 50-74%, or 75-100% of workers through contracting. Wages+Benefits cover wages, bonuses and payment (i.e. total labor costs). 95% confidence intervals plotted with robust ses.
Figure 12: Contract and Full-Time Relative Wages and Plant Size Over Time

(b) Contract Relative Wage and Plant Size, Residualized: 2000 vs 2013
(c) Relative Contract Labor Wage-Plant Size Elasticity Over Time

Note: In panel (a), we consider plants which hire contract workers and and plot the non-parametric relationship between plant-size and the log relative average wage per worker between contract and permanent workers. In panel (b), we repeat the exercise but first regress the log relative average wage per worker on a set of industry-year-contract labor share bin fixed effects. We then plot the residualized relative wages against non-managerial employment. In panel (c) we run the same specification as in the previous figure and add interactions between the contract X year dummies with log non-managerial employment. We then plot the coefficients on the contract X year X log non-managerial employment. 95% confidence intervals plotted with robust ses.
Figure 13: Contract and Full-Time Wages and Plant Size Over Time

(a) Contract Wage - Contract Employment Elasticity Over Time

(b) FT Wage - FT Employment Elasticity Over Time

(c) 1990 Staffing and the FT Wage Elasticity

Note: In panel (a) we regress the log average contract wage on log plant number of non-managerial workers interacted with year dummies (as well as a set of industry-year-contract labor share bin fixed effects) and plot the employment-year coefficients. In panel (b) we do the same for the wages of full time workers. Panel (c) regresses log average full time wage on a full interaction of log non-managerial employment, log 1990 staffing and year dummies, as well as a set of district, state-year, industry-year-contract labor bin fixed effects and 1990 district characteristics interacted with year fixed effects. The triple interaction coefficients are plotted, and are interpreted as the change in the full-time wage plant size elasticity in a given year for a 1% increase in the 1990 staffing measure, relative to the omitted category of 1998. 95% confidence intervals plotted with robust ses, except for panel (c) which clusters standard errors at the district-year.
Figure 14: Benefits and Plant Size Over Time

(a) Contract Wage - Contract Employment Elasticity Over Time

(b) FT Wage - FT Employment Elasticity Over Time

Note: Panel (a) plots the non-parametric relationship between the probability a plant pays zero benefits to all workers (non-managerial and managerial) against plant size. Panel (b) plots the log benefits paid to full-time workers divided by their wage bill against the number of full-time workers employed in the plant. Log relative benefits are first demeaned by industry years. Benefits to all workers are provided in all years of the data; benefits by worker category are in 1999-2007 only.
## Appendix Tables

Table A.1: APL/APK-Firm Size Relationship and 1990s Reform

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<th>logAPL</th>
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<td>Log L</td>
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<td>0.082***</td>
<td>0.018</td>
<td>0.032***</td>
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<td>(0.013)</td>
<td>(0.008)</td>
<td>(0.015)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>Reform</td>
<td>-0.089*</td>
<td>-0.369***</td>
<td>-0.042</td>
<td>0.125**</td>
</tr>
<tr>
<td></td>
<td>(0.049)</td>
<td>(0.050)</td>
<td>(0.063)</td>
<td>(0.057)</td>
</tr>
<tr>
<td>Log L X Reform</td>
<td>0.042***</td>
<td>0.109***</td>
<td>0.005</td>
<td>-0.049***</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.014)</td>
<td>(0.018)</td>
<td>(0.018)</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.29</td>
<td>0.29</td>
<td>0.07</td>
<td>0.07</td>
</tr>
<tr>
<td>$N$</td>
<td>401,712</td>
<td>401,712</td>
<td>386,147</td>
<td>386,147</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Reform Measure</th>
<th>Delicense</th>
<th>FDI</th>
<th>Delicense</th>
<th>FDI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Industry FE</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Year FE</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
</tbody>
</table>

Note: Observations at the firm-year level. Data covers 1985-1997. In columns (1) and (2) outcome is log APL, where employment is measured as non-managerial workers. In columns (3) and (4) outcome is logAPK. Log L is log non-managerial employment. In columns (1) and (3), reform measure is a dummy equal to one if all or part of the 3-digit industry is delicensed in that year. In columns (2) and (4), reform measure is the fraction of products open to automatic approval of FDI. Both measures from Aghion et al. (2008). Standard errors clustered by industry-year. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$
### Table A.2: District Correlates with Staffing Measure

<table>
<thead>
<tr>
<th></th>
<th>Pos. Staffing</th>
<th>In Staffing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ln District Employment</td>
<td>0.565***</td>
<td>0.188***</td>
</tr>
<tr>
<td></td>
<td>(0.110)</td>
<td>(0.069)</td>
</tr>
<tr>
<td>Ln Avg Firm Size</td>
<td>-0.020</td>
<td>0.056</td>
</tr>
<tr>
<td></td>
<td>(0.058)</td>
<td>(0.036)</td>
</tr>
<tr>
<td>Manuf Emp Share</td>
<td>0.034</td>
<td>0.042***</td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>Manuf Formal Emp Share</td>
<td>0.023</td>
<td>0.050***</td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td>(0.013)</td>
</tr>
<tr>
<td>Share Young Firms</td>
<td>-0.010</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>(0.020)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>Size Diff Ln APL</td>
<td>0.315</td>
<td>-0.187</td>
</tr>
<tr>
<td></td>
<td>(0.195)</td>
<td>(0.127)</td>
</tr>
<tr>
<td>Size Diff Ln FT Wage</td>
<td>-0.010</td>
<td>-0.049</td>
</tr>
<tr>
<td></td>
<td>(0.060)</td>
<td>(0.038)</td>
</tr>
</tbody>
</table>

State FE: X X

Note: Table reports coefficients from regressions of the outcome variable in each row on staffing measure in each column. All variables correspond to levels in 1990. In column (1) staffing measure is a dummy for whether the district has any staffing employment in 1990. Column (2) uses the weighted staffing measure from our baseline specification. In row (1), the outcome is log district total employment in 1990 from the economic census. Row (2) uses log average formal manufacturing firm size from the ASI. Row (3) reports results for the manufacturing share of all employment in the district, while row (4) uses the manufacturing share of all formal employment (defined as at establishments with more than 10 workers). In row (5) the outcome is the share of all firms in the district younger than 5. Row (6) and (7) report results for the difference in logAPL and log Wage between firms with more or less than 50 workers, where employment is defined by non-managerial workers. For outcomes in ASI sample includes 367 districts with non-missing observations for each outcome. For EC outcomes, sample includes 404 districts with non-missing observations. Robust standard errors reported in parentheses. * p < 0.1; ** p < 0.05; *** p < 0.01.

### Table A.3: Staffing Industry Over Time

<table>
<thead>
<tr>
<th>Year</th>
<th>Establishments</th>
<th>Employment</th>
<th>Employment Index</th>
</tr>
</thead>
<tbody>
<tr>
<td>1990</td>
<td>219</td>
<td>1339</td>
<td>1</td>
</tr>
<tr>
<td>1998</td>
<td>1138</td>
<td>7679</td>
<td>5.51</td>
</tr>
<tr>
<td>2005</td>
<td>12030</td>
<td>53669</td>
<td>16.52</td>
</tr>
<tr>
<td>2013</td>
<td>18669</td>
<td>83808</td>
<td>19.82</td>
</tr>
</tbody>
</table>

Note: Source is from the Economic Census. Columns total employment and establishments under the 4 digit NIC code associated with staffing firms. Employment reported is workers employed directly in the operations of the staffing establishment, rather than contract workers provided to third parties. Last column indexes total employment to its level in 1990.
B Appendix Figures

Figure B.1: Manufacturing vs Services Plant Size Distributions Over Time

(a) Manufacturing

(b) Services


Figure B.2: APK and Firm Size: 2000 vs 2013

Note: Plot contains results from non-parametric regression of log APK on log Employment using Epanechnikov kernel with a bandwidth of 0.6, where employment is the number of non-managerial workers. LogAPK is residualized by industry and year fixed effects before running the regression.
Figure B.3: APwL-Size Elasticity Over Time

(a) Elasticities by Year

(b) Cross-Section by Year

Note: Panel (a) shows elasticity of log(APwL) to log(wL) in each year. APwL is measured as value added over the total cost (wages, bonuses and benefits) of non-managerial workers, while wL is the total cost of those workers. Regression is the same as that reported for the APL and APK plots in the main text. Panel (b) shows the cross-sectional relationship non-parametrically in each year, where logAPwL is first demeaned by industry and year fixed effects. Confidence bands are omitted for clarity.
Figure B.4: Staffing Industry Growth Over Time

Note: Data is from the Economic Census. Jammu and Kashmir and parts of Madhya Pradesh missing in 1990 census.
Figure B.5: Sales vs Revenue Growth Dispersion in Large Plants

Note: Plot features the standard deviation of employment and sales growth in each year relative to 1994. Both variables detrended by industry and year fixed effects before collapsing. Only plants with more than 100 non-managerial workers included.

Figure B.6: Sales vs Revenue Growth Dispersion in Large Plants

(a) Sales Event Study

(b) Share of Output Accounted by Firm Size Bins

Note: Panel (a) shows the event study for firm sales constructed in the same way as the main ones in the paper. Panel (b) plots the share of each 5-digit ASICC product code category produced by firms in each non-managerial employment bin (averaged across all products).
C Theory Appendix

Value Function

Over a small period of length $\Delta$, the discretized Bellman equation for type $k \in \{L, H\}$ is

$$V_{k,t}(Q_t) = \max_{x,(\ell_j)} \left\{ \Delta \left[ (q_j\ell_j)^{\frac{\sigma-1}{\sigma}} P_t^{\frac{\sigma-1}{\sigma}} Y_t^{\frac{1}{\sigma}} - w_t^h \ell_j - w_t^h x^{\frac{1}{1-\beta}} \theta_k^{-\frac{1}{1-\beta}} \right] + \right\} \sum_j \left[ (1 - \rho \Delta) \left[ V_{k,t+\Delta} (Q_t \setminus \{q_j\}) - \kappa_k w_t^h \ell_j \right] + \right] (1 - \tau \Delta - x \Delta) V_{k,t+\Delta} (Q_t) \right\}.$$ 

Subtract $(1 - \rho \Delta) V_k(Q)$ from both sides, rearranging, dividing by $\Delta$ and letting $\Delta \to 0$ yields the HJB equation

$$\rho V_{k,t}(Q) - \dot{V}_{k,t}(Q) = \max_{x,(\ell_j)} \left\{ \tau \left[ V_{k,t} (Q \setminus \{q_j\}) - \kappa_k w_t^h \ell_j - V_{k,t}(Q) \right] + x [E_q [V_{k,t} (Q \cup q)] - V_{k,t}(Q)] \right\}.$$ 

Dividing by $Y_t$ and writing in terms of the normalized value function yields the expression in the text.

Proof of Lemma 1

Proof. Make the conjecture. Then we can write

$$\rho A_k \sum_{q_j \in Q} q_j^{\sigma-1} + \rho n B_k = \left\{ \sum_{q_j \in Q} \pi_k q_j^{\sigma-1} - \tau \left( A_k q_j^{\sigma-1} + B_k \right) \right\} + n \max_{x \geq 0} \left\{ x (A_k E [q^{\sigma-1}] + B_k) - \omega^h x^{\frac{1}{1-\beta}} \theta_k^{-\frac{1}{1-\beta}} \right\}.$$ 

Equating the coefficients on $q_j^{\sigma-1}$ and everything else we need that

$$\rho A_k = \pi_k - \tau A_k$$

$$\rho n B_k = -\tau n B_k + n \max_{x \geq 0} \left\{ x (A_k E [q^{\sigma-1}] + B_k) - \omega^h x^{\frac{1}{1-\beta}} \theta_k^{-\frac{1}{1-\beta}} \right\}.$$ 

The first line implies

$$A_k = \frac{\pi_k}{\rho + \tau}.$$ 

From the second line, we find that optimal innovation intensity is given by

$$x_k = \frac{1}{\theta_k^{\frac{1}{\beta}}} \times \left( \frac{A_k E [q^{\sigma-1}] + B_k}{\omega^h} \right)^{\frac{1-\beta}{\rho}}.$$
where $\tilde{\beta} = (1 - \beta)^{\frac{1-\rho}{\beta}}$. Substituting this back and rearranging, we find that

$$(\rho + \tau)B_k = \tilde{\beta} \theta_k \left( \frac{A_k E[q^{\sigma-1}] + B_k}{(w^H)^{1-\beta}} \right)^{\frac{1}{\beta}}$$

Proof of Lemma 2

Proof. Over any small period, three things can happen to a product $q_j$: it can be innovated by type-$H$ (w.p. $(\alpha x^e + \mu_H x^H)\Delta$), innovated by type-$L$ (w.p. $((1 - \alpha) x^e + \mu_L x^L)\Delta$) or it stays the same (w.p. $1 - \Delta \tau$). Note that we have distinguished between who innovates over the product, since this will determine the MRPL in the next period. Defining $\tilde{A}_t = A_t^{\sigma-1}$ so that $\frac{\dot{A}}{A} = \frac{1}{\sigma-1} \frac{\dot{A}}{A}$, we have

$$\tilde{A}_{t+\Delta} = \int_0^1 \left[ (\alpha x^e + \mu_H x^H)\Delta \left( 1 + \lambda q_j \frac{MRPL_t}{MRPL_H} \right)^{\sigma-1} \right] dj + ((1 - \alpha) x^e + \mu_L x^L)\Delta \left( 1 + \lambda q_j \frac{MRPL_t}{MRPL_L} \right)^{\sigma-1} dj + (1 - \tau \Delta) \left( q_j \frac{MRPL_t}{MRPL(q_j)} \right)^{\sigma-1} dj$$

Subtract $\tilde{A}_t$, divide by $\tilde{A}_t$, and taking the limit as $\Delta \to 0$ yields the expression in the text.