Contract Labor and Firm Growth in India

Marianne Bertrand
University of Chicago Booth, NBER and CEPR

Chang-Tai Hsieh
University of Chicago Booth, NBER and CEPR

Nick Tsivanidis*
University of California, Berkeley

August 2021

Abstract

India's Industrial Disputes Act (IDA) of 1947 requires firm with more than 100 workers to pay large costs if they shrink their employment. Since the early 2000s, large Indian manufacturing firms have increasingly relied on contract workers who are not subject to the IDA. By 2015, contract workers accounted for 38% of total employment at firms with more than 100 workers compared to 20% in 2000. Over the same time period, the thickness of the right tail of the firm size distribution in formal Indian manufacturing plants increased, the average product of labor for large firms declined, the job creation rate for large firms increased, and the probability that large firms introduce new products rose. We provide evidence that these outcomes were caused by an increased reliance on contract labor among large establishments. A model of firm growth subject to firing costs suggests the rise of contract labor increased TFP in Indian manufacturing by 7.6%, occurring all through a one-time reduction in misallocation between large and small firms with negligible change in the long-run growth rate.

*We thank the University of Chicago's India Trust for financial support, Manish Sabharwal for helping us understand the labor contracting landscape in India, seminar participants at Cornell, MIT and Berkeley for helpful comments, and Kazuatsu Shimizu for superb research assistance.

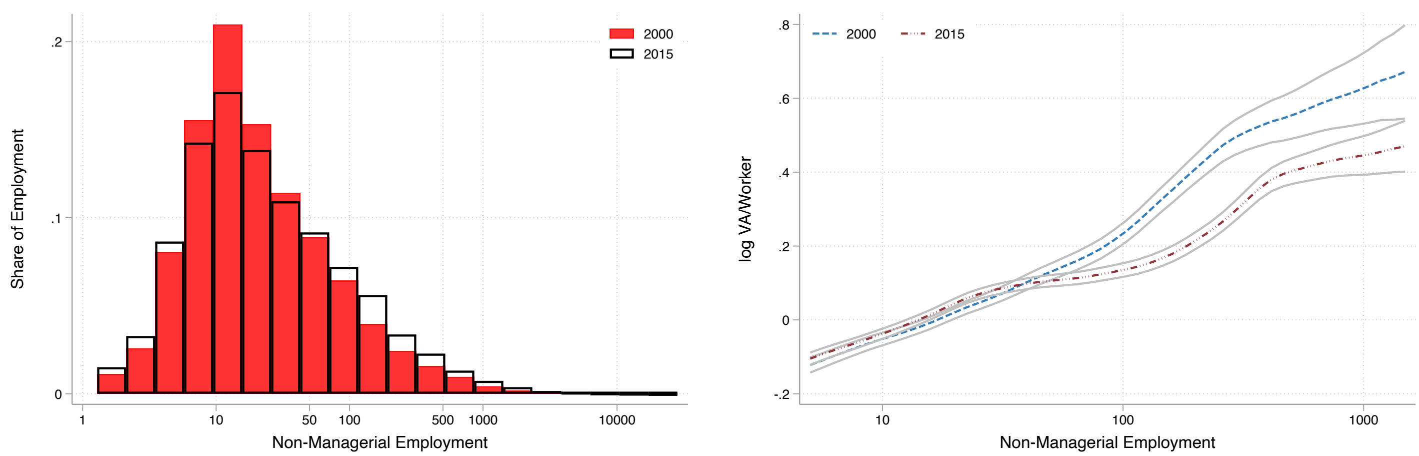
1 Introduction

Many observers have pointed to the Industrial Disputes Act (IDA) of 1947 as an important constraint on growth in India. The IDA requires firms with more than 100 workers that shrink their employment to provide severance pay, mandatory notice, and obtain governmental retrenchment authorization.[1] 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. Second, the higher costs faced by large firms in retrenching workers may dissuade them from undertaking risky investments in order to expand, which may be one of the forces behind the low life-cycle growth of Indian firms.[2]

Figure 1: Firm Size Distribution and VA/Worker by Size, 2000 vs. 2015

(a) Firm Size Distribution

(b) VA/Worker vs. Firm Size



Note: Left panel shows employment-weighted distribution of firm employment. Right panel shows coefficients and 95% confidence intervals from non-parametric regressions of log VA/Worker on log employment using Epanochnikov kernel with a bandwidth of 0.6. Employment is the number of non-managerial workers. Log VA/Worker is residualized by industry and year fixed effects.

This paper argues that the constraints on large firms have diminished since the early 2000s, despite the fact that there has been no change in the IDA.[3] Consider the evidence in Figure 1. The left panel shows that the thickness of the right tail of formal Indian manufacturing increased between 2000 and 2015. The right panel shows that average value-added/worker is increasing in firm employment in 2000 and 2015, but this relationship is more attenuated in 2015 compared to 2000,

[1] A 1976 amendment to the IDA made layoff, retrenchment and closure illegal for all firms with more than 300 workers. This coverage was extended in 1982 to all firms with more than 100 employees.

[2] See Hsieh and Olken (2014) on the firm-size distribution in India and Hsieh and Klenow (2014) for evidence on low life-cycle growth in Indian manufacturing.

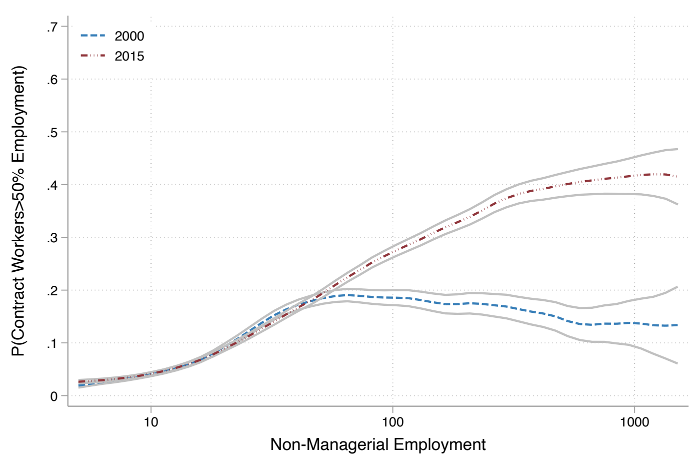
[3] The reforms that started in 1991 mostly dismantled the reservations for small-scale industries and the industrial licensing laws. The Industrial Relations Code of 2020 consolidates and updates the Industrial Disputes Act of 1947, the Trade Unions Act of 1926, and the Industrial Employment Act of 1946. It has yet to come into force.

particularly for firms with more than 100 workers. If the marginal product is proportional to the average product of labor, and profit-maximizing firms equate the marginal product of labor to the cost of labor, then this suggests that the effective cost of labor has diminished for larger Indian firms compared to smaller firms.[4]

We argue the main force behind the decline in labor constraints faced by large Indian firms since the early 2000s is that these firms increasingly rely on contract workers hired via staffing companies. The IDA only applies to a firm's full time employees; contract workers are *not* the firm's employees for the purposes of the IDA. The contract workers are employees of the staffing companies, and the staffing companies themselves have to abide by the IDA. This loophole provides customer firms with the flexibility to return the contract workers to the staffing company without being in violation of the IDA.

Figure 2: Contract Labor Use and Firm Size: 2000 vs 2015

(a) Any Contract



Note: Plot shows point estimates and 95% confidence intervals from non-parametric regression of the probability a plant hires more than 50% of its non-managerial workers through contractors on (log) non-managerial employment.

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. Figure 2 shows the probability that contract workers account for more than 50% of total firm employment as a function of total firm employment. Among smaller firms, there has been no discernible 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, particularly among firms with more than a 100 workers.

We argue that a decision by the Indian Supreme Court in 2001 played an important role in explaining the explosion of contract labor in India, particularly on how large firms came to use temporary

[4]Figures 1 and 2 are based on the micro-data from India's ASI. We describe this data in Section 3.

workers with much greater intensity.[5] Prior to this decision, it was unclear whether firms who were caught improperly using contract workers would have to absorb these workers into regular employment. This plausibly made large firms reticent to rely on contract labor. This 2001 Supreme Court decision clarified that this was not the case. We show that there was a discrete change in the use of contract workers by large firms, in the employment share of large firms, and in the gap in labor productivity between large and small firms after 2001. In addition, these changes were more pronounced in pro-worker states and for firms with better access to staffing firms prior to the decision.

There are two main channels through which a greater reliance on contract workers may have led to the expansion of large firms and the decline in the value-added per worker of these firms. First, the IDA places size-dependent restrictions on the ease of firing workers. Because these firing costs are lower 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 as an 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 districts where contract workers are more available (measured either through the share of contract workers or access to staffing firms in the period before the shock) 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 of the 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 2015. This decline comes from two forces. First, the relative cost of contract labor compared to permanent labor is lower at larger firms and hence the average cost of labor goes down for larger firms as they tap more into the contract labor pool. Second, 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 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

[5] The Supreme Court Case is "Steel Authority of India Ltd. vs. National Union Water Front Workers."

investment, in that they become more likely to change their product mix.

We use a model of creative destruction with heterogeneous firms to quantify the effect of contract labor in the presence of the IDA. The model features two types of firms. Innovative, high-type firms expand over time by producing new products, while stagnant low-type firms do not innovate and remain small. We model the IDA as an adjustment cost faced by high-type firms whenever they fire workers. The anticipation of future retrenchment causes large firms to hire a sub-optimally 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). We model the use of contract workers by large firms by assuming that firms subject to the IDA can circumvent firing costs by hiring contract workers after paying a fixed cost.[6] We estimate the reduction in this fixed cost that matches the rise in the share of contract labor within large firms over the period. By simulating a counterfactual in which only this fixed cost changes while holding all other aspects of the model constant (including the retrenchment costs due to the IDA), we estimate the effect of the growing use of contract workers by large firms on the gap in value-added per worker between large and small firms, aggregate TFP and the innovation rate.

We find that the use of contract labor explains all of the decline in the gap in value-added per worker between large and small firms seen in Figure 1. This decline accounts for 7.6% of the overall increase in manufacturing TFP over this period, by reducing the misallocation of resources between productive and unproductive firms. However, our results suggest the aggregate growth rate did not change due to the proliferation of contract labor. On the one hand, the model suggests firms subject to the IDA innovate more as its bite is reduced via the increased availability of contract workers. On the other, entrants (who are more likely to be of low-type) respond to this increased competition by innovating less. The empirical implications of both these channels - increased innovation by large incumbents and a reduced employment share of entrants - are both borne out in the data despite not being targeted by the model. On net, these two effects cancel each other out with no net impact on aggregate innovation (and hence aggregate growth).

This paper makes four main contributions. First, it contributes to the small but growing literature on the rise of non-standard work arrangements. Katz and Krueger (2019) report about a five percent increase in the use of alternative work arrangements in the US economy between 2005 and 2015.[7] Goldschmidt and Schmieder (2017), Dube and Kaplan (2010), and Drenik et. al. (2020) document the rise and wage effects of temporary work arrangements in Germany, Denmark, and Argentina, respectively. Relative to this work, we exploit a quasi-experimental legal change in India that drove the proliferation of temporary work arrangements. This allows us to empirically trace out its effects

[6] The model does not take into account the effect of hiring contract workers on wages of permanent workers. We discuss its implications in Section 6.

[7] Although Abraham and Amaya (2018) discuss the limitations of U.S. labor force surveys in capturing this phenomenon.

on firms and workers.

Second, we develop a model of creative destruction with heterogeneous firms and size-dependent firing costs to quantify their impacts on aggregate TFP. A strand of existing theoretical work seeks to quantify the effects of such policies (e.g. Hopenhayn and Rogerson, 1993; Restuccia and Rogerson, 2008; Guner, Ventura and Xu, 2008). However in these models firm productivity is an exogenous characteristic. Thus they do not account for how such policies might affect productivity growth via firms' innovation decisions, which we show respond to relaxation of firing costs in the data. To make progress on this front, we extend recent models of Schumpeterian growth following Klette and Kortum (2004) to incorporate size-dependent firing costs.[8] This allows us to quantify the total effect of these frictions on TFP, both through impacts on static misallocation and long-run productivity growth.

Third, we provide new evidence on the source of misallocation in developing countries. A large literature has documented misallocation as a potential source of low TFP in developing countries (e.g. Hsieh and Klenow, 2009; Restuccia and Rogerson, 2017). Much work since has sought to isolate particular causes of misallocation.[9] This paper provides evidence that it is large rather than small firms who face higher frictions in labor markets, and show this gap is driven in part by size-dependent firing costs using a quasi-experimental policy change that reduced these frictions during the 2000s in India.[10]

Lastly, our paper contributes to the literature on the economic impact of labor regulation in India.[11] We provide new evidence on how large firms subject to the IDA were able to circumvent this law by employing contract workers, and the impacts of this de facto reduction in labor regulation on firm behavior.

The rest of the paper is organized as follows. Section 2 lays out the institutional background and describes the legal framework underpinning the use of contract labor in India. Section 3 describes the data sources. Section 4 provides various empirical tests of a causal relationship between the

[8] E.g. Acemoglu et al. (2018), Akcigit and Kerr (2018), Akcigit, Alp and Peters (2021).

[9] Sources of misallocation studied in the literature include microcredit (Kaboski and Townsend, 2011), financial frictions (Buera, Kaboski and Shin, 2011; Midrigan and Xu, 2014; Bau and Matray, 2021), contract enforcement (Boehm and Oberfield, 2020), reservation laws (Garcia-Santana and Pijoan-Mas, 2014; Martin, Nataraj, and Harrison, 2017), electricity (Alcott, Collard-Wexler and OâConnell, 2016)

[10] Gourio and Roys (2014) and Garicano, Lelarge and Van Reenen (2016) study the effects of size-dependent labor regulations in France.

[11] Fallon and Lucas (1991, 1993) show that the 1976 amendment of the IDA, which mandated firms employing 300 o rmore workers to request permission from the government prior to retrenchment, lowered formal employment by 17.5%.Dutta Roy (2004) also finds that firms subject to the IDA face substantial adjustment costs, but that the 1982 amendment to the IDA, which extended the prohibition to retrench workers without government authorization to firms that employed 100 or more workers, did not change these costs. Besley and Burgess (2004) exploit the state-level variation induced by the state-level amendments to the IDA, and find that states which amended the IDA in a pro-worker direction experienced lowered output, employment, investment and productivity in formal manufacturing. Hasan, Mitra and Ramaswamy(2007) and Aghion et. al. (2008) show that pro-worker states are less responsive to trade form and industrial licensing reform, respectively.

rise in contract labor and the increase in firm size and decline in average product labor at larger firms. In Section 5, we investigate two mechanisms via which contract labor may have freed up firm growth: reduction in labor adjustment costs and reduction in the cost of labor. Section 6 develops and estimates our structural model. We conclude in Section 7.

2 Contract Labor in India

The key piece of labor legislation in India is the Industrial Disputes Act of 1947 (IDA, 1947). The IDA lays out the conditions for hiring and retrenching workers, as well as for the closure of establishments. A 1976 amendment to the IDA stipulated that all firms with more than 300 workers needed to get government authorization for any layoff, retrenchment, or closure. This coverage was subsequently extended in 1982 to all firms with more than 100 employees. Unapproved separations carry a potential punishment of both a substantial fine and a prison sentence for the employer.[12] Other aspects of the IDA and related laws impose additional costs on firms with a large number of full-time employees.[13]

However, the IDA provides one potential loophole for large establishments to skirt its requirements. Contract workers are not considered employees of the establishments in which they work and are therefore exempt 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. Indian legislators realized this loophole and began to address it starting in 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.

[12] Actual compensation for retrenchment if granted 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.

[13] For example, the Industrial Employment (Standing Orders) Act 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 employer 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.

Section 10 of the Contract Labor Act was written to specifically limit the use of contract workers as a loophole around the IDA's requirements. This section 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 its *Steel Authority of India Limited v. National Union Water Front Workers* judgement (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."

Staffing companies are subject to 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. The contract labor system thus shifts retrenchment liability from the client firm to the staffing firm. The staffing firm may be more willing to take on this liability if they have many clients they work with and can therefore pool changes in labor demand across multiple firms.

3 Data

Our primary source of data is the Annual Survey of Industries (ASI) from 1983 to 2015, as conducted by India's Statistical Office (NSSO).[14] 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.[15] The data comes with establishment identifiers for the years between 1993 and 2015 and with district identifiers for all years until 2009. The ASI does not provide firm identifiers so we cannot group establishments into firms. Data is collected 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 that year and March 31 of the following year.

The key variables we rely on for our analysis are value-added, employment, labor compensation, book value of capital, main industry of the establishment, and district identifier. The ASI provides information on the number of workers directly employed by the establishment and workers hired through contractors (hereafter referred to as "full-time" and "contract" workers). Wages, bonuses, and benefits for all workers are reported in all years, and a breakdown between full-time and contract workers is provided in a subset of years.[16] The ASI also provides information on the number of

[14]While ASI data is currently available until 2017, we restrict the time series to 2015 because of other shocks to the Indian economy in subsequent years, in particular the 2016 banknote demonetization.

[15]The 1948 Factories Act requires that establishments with more than 20 workers be formally registered (the threshold is 10 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 in the ASI "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."

[16]Wages for full-time and contract workers are separately provided between 1998 and 2015; the same is true for bonuses and benefits between 1998 and 2007.

"managerial" and "non-managerial" workers, as well as wages, bonuses, and benefits for these two types of workers.

We supplement the ASI with three additional data sources. First, we use the Economic Census 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 grid-points at 1/2 degree intervals (Matsuura and Willmott 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).

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

This section provides evidence that the rise in contract labor reduced constraints and increased growth among large manufacturing plants in India. First, we conduct an event study analysis around the SAIL judgement in 2001 to show that adoption of contract labor rose and constraints on large firms fell following this decision. Second, we show these changes were more pronounced in pro-worker states and in districts with greater proximity to the staffing industry ten years prior to SAIL in 1990. Since SAIL benefited firms with better access to contract workers via staffing companies, this supports the idea that the break in aggregate trends around the SAIL decision was due to increased adoption of contract workers. Third, we conduct within-firm event studies to examine changes in outcomes around the year they first hire contract workers.

4.1 Effect of SAIL Event in the Time Series

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 motivating patterns documented in the introduction.

Figure 3 shows the probability that large firms employ contract workers in each year. 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).[17] We then plot the estimated firm size coefficients for each year, as well as the 95% confidence intervals. Panel (a) in Figure 3 shows that larger firms have always been more likely to rely on some contract labor and that this greater reliance has been growing steadily over time. Panel (b) in Figure 3

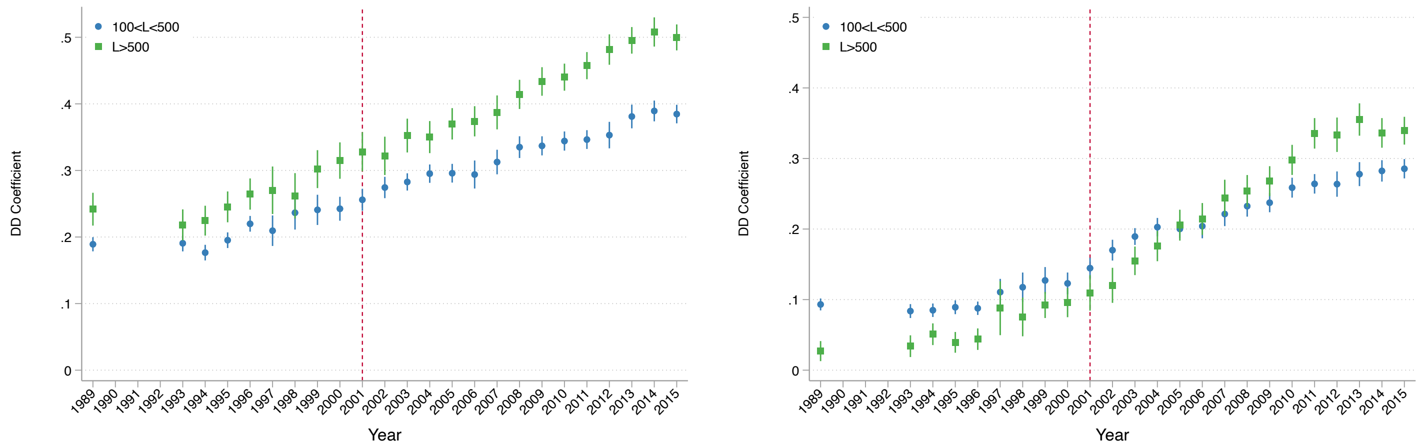
[17] Also included in the regression are industry and year fixed effects.

replicates the same exercise as panel (a) but focuses on whether contract labor represents at least 50% of a firm's non-managerial labor. This 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, increased after 2001.

Figure 3: SAIL and Contract Labor Use by Firm Size

(a) Any Contract

(b) Contract>50% Employment

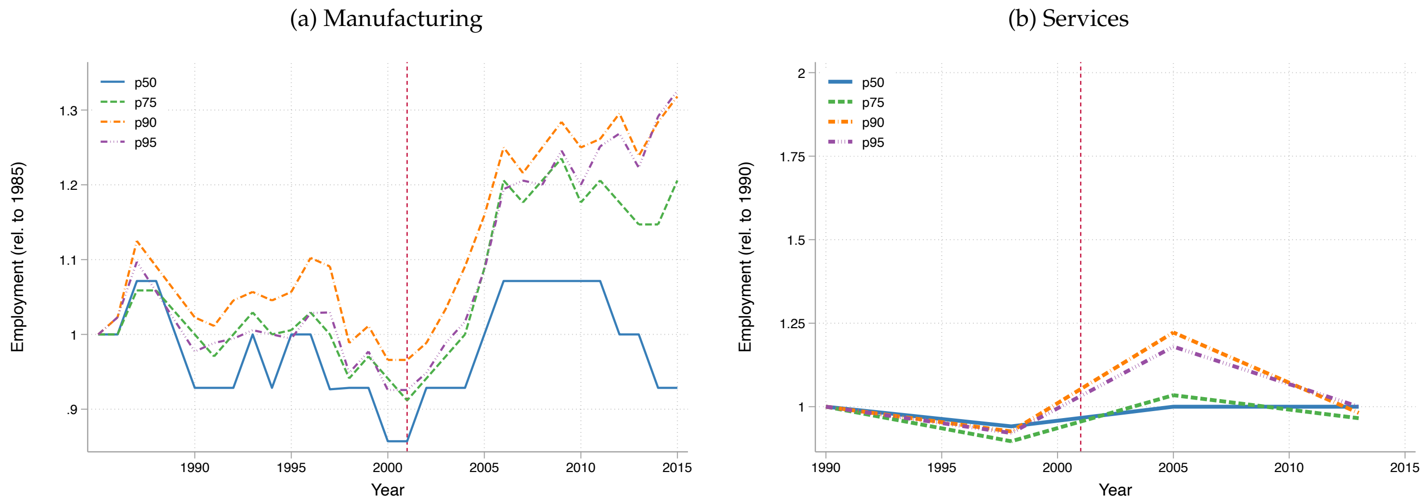


Note: Plot shows coefficients and 95% confidence intervals on size by year interactions from a regression of a dummy for whether a plant hires more than a certain fraction of non-managerial workers through contractors on year, industry, and size by year interactions. Size is defined by non-managerial employment bins of 0-100, 100-500 and 500+ workers (0-100 are the omitted category). Panels (a) and (b) construct the contract use dummies for whether a plant hires more than 0 or 50% of workers through contractors respectively.

We next examine whether the timing of the changes in the firm size distribution also coincides with the SAIL case. Figure 4 plots the trend in the 50th, 75th, 90th and 95th firm size percentiles between 1985 and 2015 for manufacturing (left panel) and services (right panel). The left panel confirms an impressive and sustained growth in the upper percentiles of manufacturing establishments starting around SAIL. The 90th and 95th percentiles of firm size, while smaller in 2000 than in 1985, have grown steadily since 2001. The 95th percentile firm has 43 percent larger employment in 2015 compared to 2000, while the 90th and 75th percentile firms have 36 and 28 percent larger employment. The right panel shows the establishment size distribution in services over this time period. While the IDA as a whole applies to all sectors, Section 5, which covers the majority of restrictions on retrenchments, applies only to manufacturing establishments, mines, and plantations with more than 10 workers. As can be seen, there was no comparable change in the size distribution of establishments in services.[18]

[18] See B.3 for a comparison of sectors within the Economic Census data only. The y-axis of panel (b) in Figure 4 is chosen to match the scale of the changes in the manufacturing sector in the Economic Census depicted in panel (a) of Figure B.3. The Economic Census data considers the univserse of formal and informal firms while the ASI reports only formal employment, and therefore the changes in percentiles within manufacturing differs.

Figure 4: Manufacturing vs Services Plant Size Distributions Over Time

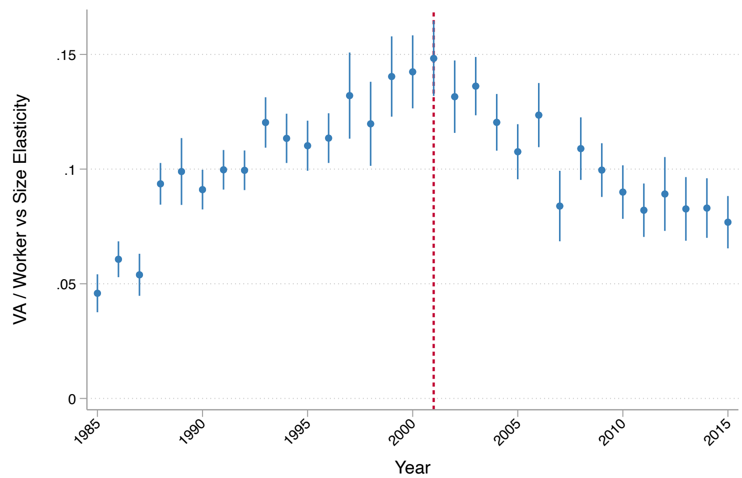


Note: Plot shows percentiles of plant employment in manufacturing and service sector establishments from the ASI (manufacturing) and Economic Census (services). ASI data is annual, Economic Census data is from 1990, 1998, 2005 and 2013. See B.3 for a comparison using only the Economic Census data.

Figure 5 examines the timing of the change in the elasticity of value-added per worker with respect to firm size. Recall from the introduction that if the marginal product of labor is proportional to the average product and firms equate marginal products with factor costs, this elasticity measures the extent to which large firms face higher effective costs of labor than small firms. We regress log value-added per worker on log employment interacted with year dummies (and a full set of industry and year fixed effects) from 1985 to 2015, and plot the coefficient on log employment in each year. The elasticity shows a persistent increase between 1985 and the early 2000s, possibly because the reforms that began in 1991 removed most licensing restrictions and reservations for small firms, which may have had the effect of making the labor constraints of the IDA more binding.[19] More importantly, Figure 5 shows that the elasticity of the average product of labor to firm size fell after the early 2000s, possibly due to the SAIL event.

[19] Appendix Table A.3 shows that the elasticity of the average product of labor to firm size increased by more in industries subject to delicensing.

Figure 5: Elasticity of VA/Worker to Firm Size



Note: Plot shows coefficients and 95% confidence intervals from regressions of log VA/Worker (APL) 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.

4.2 Heterogeneity of SAIL Event

In this section, we examine the heterogeneity in the impact of the SAIL event to the latent demand for and the supply of contract workers. Figure 6 probes for evidence of heterogeneity across Indian states based on the demand for contract workers. The figure replicates the estimates shown in Figure 3 separately in pro-worker (panel (a)) and pro-employer (panel (b)) states.[20] It is apparent that the reaction to SAIL among IDA-subject firms was greater in pro-worker states where presumably the IDA constraints were more binding than it was in pro-employer states.

We next examine heterogeneity across Indian districts based on the initial supply of staffing companies in the district. The Contract Labor Act requires that firms access contract workers through government licensed contractors or staffing companies. It is therefore likely that the SAIL shock we identified in the time series was larger for firms that were located geographically closer to such staffing centers.

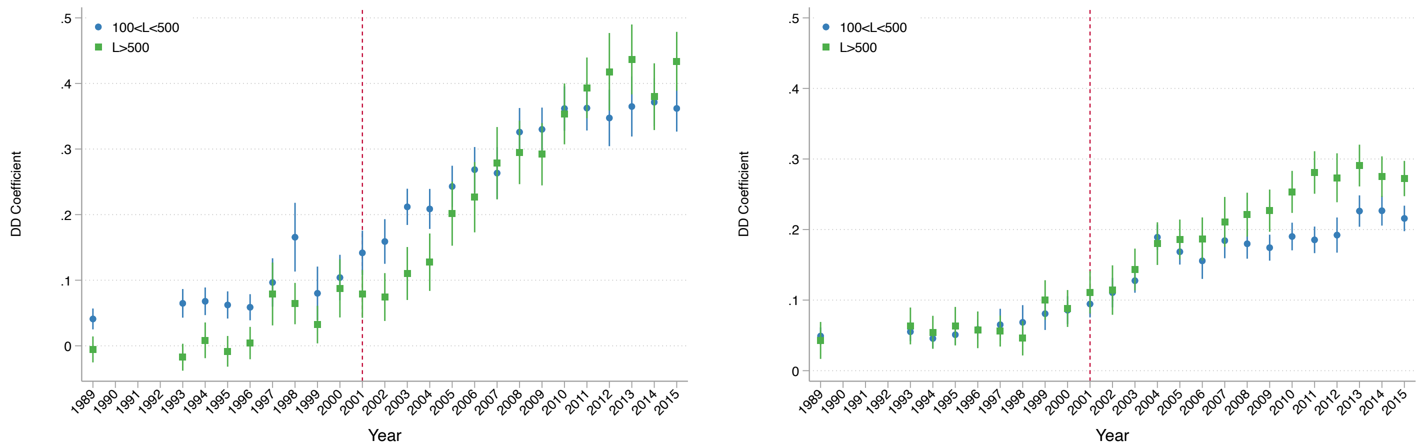
To measure the supply of staffing firms uncorrelated with demand-side forces after the SAIL decision, we measure a district's proximity to staffing firms in the 1990 Economic Census. We use a distance-weighted proximity measure rather than the staffing employment within a district to capture that, although most districts in 1990 did not have establishments providing staffing services, those close by still had access to these firms and the staffing industry as a whole radiated outwards from these initial clusters over time.[21] We measure a district's proximity to staffing employment in

[20] We use Besley and Burgess (2004)'s measure of worker regulation in the state.

[21] See Figure B.2 in the appendix. Table A.1 correlates our measure of access to staffing companies in a district in 1990 with other characteristics of the district in 1990. Districts close to more staffing employment in 1990 tend to have more overall

Figure 6: SAIL and Contract Labor Use by Firm Size:
Pro-Worker vs. Pro-Employer States

(a) Pro-Worker States (b) Pro-Employer States



Note: Plot shows coefficients and 95% confidence intervals on size by year interactions from a regression of a dummy for whether a plant hires more than 50% 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) and (b) run the specifications separately in states which are pro-worker and pro-employer according to the Besley and Burgess (2004) measures.

1990 as

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

where dist_{kd} is the number of kilometers between the centroids of districts d and k, $L_{k,1990}^{\text{Staffing}}$ is the number of workers employed by staffing firms in district k in 1990, and κ controls the rate at which the weight on surrounding staffing employment decays with distance. We exclude a district's own staffing employment since this may be endogenous to future outcome growth. We use a decay parameter of $\kappa = 0.0075$ in the main specifications, and vary this in Appendix Table A.2.[22]

Table 1 assesses whether the increase in the use of contract labor after SAIL was larger among firms located in districts that were closer to staffing employment. In particular, we regress a dummy for the 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. Table 1 shows that the 2001 SAIL shock is more pronounced in districts that

employment and a greater share of manufacturing in both total and formal employment, but otherwise look balanced in terms of other characteristics such as average firm size, the share of young firms, gap in the average product of labor or full time wages between large and small firms.

[22]The weight falls by $\kappa \times dist_{ij}$ percent for districts $dist_{ij}$ km away from each other. For example, 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. We exclude the district itself in the sum to remove an immediate source of endogeneity.

are closer to staffing centers. We also include as controls (in the even columns) interactions between year dummies and a vector of 1990 district level controls.[23] The point estimates are essentially unchanged when we include these additional controls.

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

	Any	Any	25%	25%	50%	50%
log Staffing × Post	0.016**	0.019***	0.016**	0.017***	0.015***	0.017***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)
N Obs.	627,657	608,221	627,657	608,221	627,657	608,221
N Clusters	444	403	444	403	444	403
R^2	0.19	0.19	0.19	0.19	0.18	0.18
District Controls × Year FE		X		X		X

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, and state-year and industry-year fixed effects. Standard errors clustered at the district level in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

These results suggest the aggregate shock induced by the SAIL decision led to greater contract labor adoption during the 2000s in districts with greater initial access to staffing firms in 1990. Table 2 then analyzes how firm-level outcomes of interest changed in these districts. Each entry 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 year dummies and surrounding employment in 1990 to control for the fact that places near staffing employment centers may be closer to more businesses overall.[24] Columns 3 and 4 add firm and district controls respectively (each interacted with year dummies).

Table 2 shows 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 more precise when proxying for labor inputs using total labor costs (wages, bonuses, and benefits).[25]

[23]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.

[24]We construct this using the same measure as in (4.2), but using total employment instead of staffing employment.

[25]Wage bill is the sum of wages, bonuses and benefits of non-managerial workers. See also Appendix Figure B.1.

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

	(1)	(2)	(3)	(4)
logL	0.040**	0.051***	0.046***	0.040***
	(0.016)	(0.017)	(0.013)	(0.013)
logAPL	-0.013	-0.021	-0.021*	-0.013
	(0.011)	(0.014)	(0.012)	(0.013)
logAPwL	-0.019**	-0.024**	-0.024**	-0.022**
	(0.009)	(0.012)	(0.010)	(0.011)
Wght Emp X Year FE		X	X	X
Firm Controls X Year FE			X	X
Dist Controls X Year FE				X

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. All regressions include district fixed effects, state-year fixed effects, and industry-year fixed effects. Wght Emp refers to log weighted total employment in 1990 constructed in the same way as the staffing measure. Firm controls include dummies for plant ownership and organization type as well as a polynomial in firm age. 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. Standard errors clustered at the district.* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

4.3 Firm-Year Panel Analysis

Because the ASI data includes plant identifiers from 1993 to 2013, we can also exploit this panel structure to study within-firm changes in outcomes of interest around the time the firm started to use contract labor. We report this analysis in Table 3. Each entry in the table corresponds to a different regression and reported in the cell is the coefficient on the contract labor use variable. All regressions control for state-year fixed effects and industry-year fixed effects.

Before discussing the within-firm results, we illustrate in the odd columns of Table 3 the 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 or 50 percent or more) at any time during the sample period. The entries therefore report the average difference in each outcome for plants firms that hire contract labor (in the years before they do) compared to firms that never do.

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

Table 3: Correlates of Contract Labor Hiring: Between and Within Firms

	Ever Contract	Contract	Ever Contract	Contract
log Employment	0.580***	0.354***	0.358***	0.358***
	(0.020)	(0.008)	(0.017)	(0.011)
log VA/Wage-Bill	0.165***	-0.129***	0.149***	-0.145***
	(0.012)	(0.007)	(0.014)	(0.009)
log VA/Worker	0.395***	-0.192***	0.315***	-0.220***
	(0.020)	(0.009)	(0.020)	(0.011)
Inaction	0.002	-0.036***	-0.026***	-0.041***
	(0.005)	(0.005)	(0.006)	(0.006)
Job Creation Rate	0.020***	0.122***	0.020***	0.155***
	(0.003)	(0.005)	(0.004)	(0.006)
Add Output Product	0.004	0.019***	0.010	0.021***
	(0.006)	(0.006)	(0.008)	(0.007)
Sample	All	Ever Contract	All	Ever Contract
Contract Measure	Any	Any	50%	50%
State-Year FE	X	X	X	X
Industry-Year FE	X	X	X	X
Firm FE		X		X

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. For the 50% column, the years before they first hire workers through contracting are defined as years before the firm hires 50% of workers through contracting, in which they could already hire less than 50% of workers via contracting. All regressions include state-year fixed effects and industry-year fixed effects. Inaction is a dummy equal to one if non-managerial annual employment growth is less than 10% in absolute value. Job creation rate is g_{it} for expanding firms and zero otherwise. Add Output Product is a dummy equal to one if a firm introduces a new 5 digit product to its output portfolio. Data covers 1993-2013. Standard errors clustered at the district level.* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

more dynamic in their employment: they are less likely of being in an inaction range where they do not change non-managerial employment by more than 10% in absolute value from one year to the next.

The 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 within-firm changes associated with the use of contract labor by including firm fixed effects. The results show that firms grow in size when they use contract labor (row 1), whether we define use of contract labor on the extensive (column 2) or intensive margin (column 4). These firms also experience a drop in value-added per worker after hiring contract labor (rows 2 and 3).

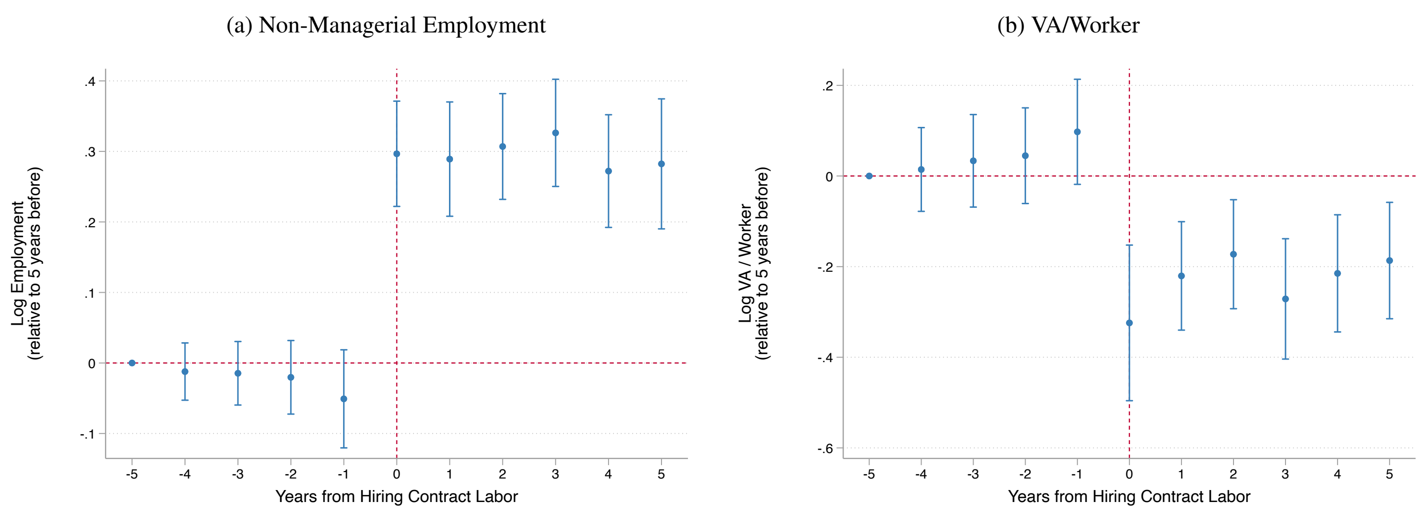
We complement this firm-year panel data analysis with event studies that allow us to visualize the evolution of these key outcomes in the years that precede and follow the first hiring of contract labor. In particular, we run the following event study specification:

$$Y_{it} = \sum_{x=\underline{x}}^{\bar{x}} \beta_x \mathbb{I}\left\{\text{Years Since First Hire}_{it} = x\right\} + \alpha_i + \gamma_{kt} + \gamma_{st} + \gamma' X_{it} + \epsilon_{it}.$$

Here α_i is a plant fixed effect, γ_{kt} , γ_{st} and X_{it} are industry-year and state-year fixed effects and a quadratic in firm age, and $\mathbb{I}\left\{\text{Years Since First Hire}_{it} = x\right\}$ is a dummy equal to one if year t is x years from when the establishment first hired contract labor. β_x will therefore identify the difference in outcome Y_{it} years before or after first hiring contract labor. We restrict the sample to firms (i) for which we observe an uninterrupted window spanning five years before and five years after they first hire contract workers and (ii) which hire contract workers for all five years following the first hire. These restrictions leave us with a sample of 337 plants. 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.

The results are presented in Figure 7. There is a sharp rise in non-managerial employment (panel (a)), as well as a sharp drop in value-added per worker (panel (b)) immediately following the hiring of contract labor. Although these event studies do not establish causality, there is no clear evidence of pre-trends in these outcomes in the years that precede the first hiring of contract labor.

Figure 7: Event Studies Around First Year of Hiring Contract Labor



Note: Plots report coefficients and 95% confidence intervals 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 only vary for establishments in our sample of 337 plants for which we observe 11 uninterrupted years, with 5 years uninterrupted data both before and after contract labor first hire, with contract workers hired in all years after the initial hire. Each coefficient is relative to the omitted category of 5 years before first hire.

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

In this section, we look for evidence for two channels through which the use of contract workers may have benefited large firms in India. First, the more widespread availability of contract workers may have prompted large Indian firms to employ more workers and undertake more risky investments because they are no longer subject to firing costs. Second, contract workers may also have increased the bargaining power of large employers with respect to their workers.

5.1 Reductions in Labor Adjustment Costs

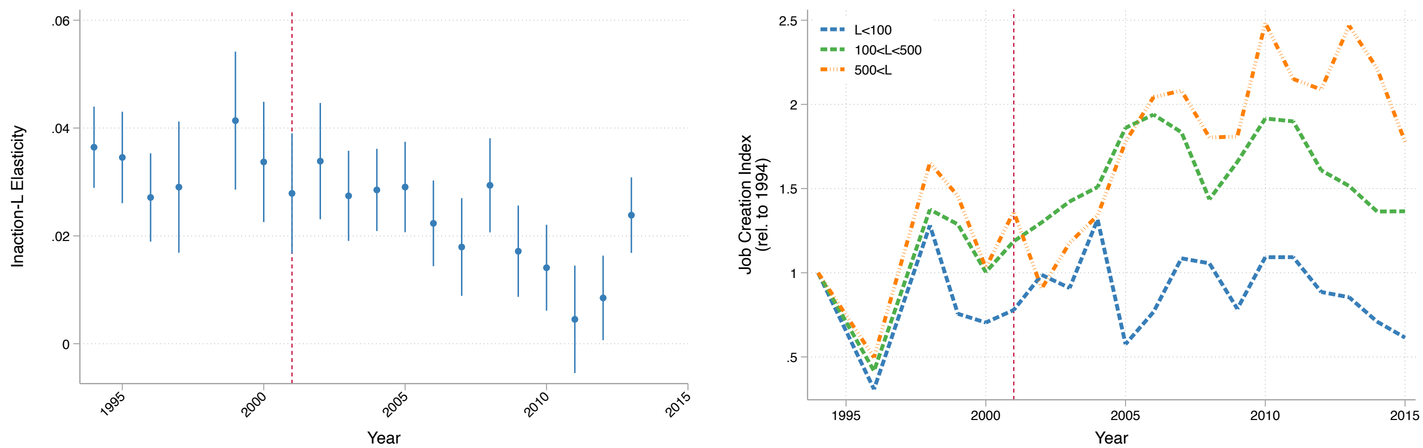
When a firm receives a positive labor demand shock that may be reversed in the future, the firing cost can make it reluctant to expand - large firms subject to a moderate positive shock today will not hire additional workers with the knowledge that they'll most likely have to fire them in the future. The firing cost could also discourage firms from undertaking risky investments. The use of contract workers, by reducing firing costs, could reduce the inaction band in employment and prompt firms to undertake risky investments. In this subsection we look for evidence consistent with these mechanisms.

Consider first the time-series around SAIL in Figure 8. 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-year and state-year dummies. Figure 8 shows the coefficients on log employment for each year. Throughout the sample period, the likelihood of inaction increases with firm size. Most relevant to us, and consistent with a decrease 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) displays the gross job creation rates by firm size over time (relative to 1994), which we define as the ratio of employment change divided by the average of firm employment at the beginning and end of each period, conditional on positive employment growth. [26] Here again, we observe an uptick in job creation by larger firms starting in the early 2000s relative to firms with fewer than 100 non-managerial workers.

[26] These are summed across firms in the 3 size bins, and plotted indexed to their value in 1994. A period is one year. With this definition the job creation rate of an entrant is 2.

Figure 8: SAIL and Employment Dynamics

(a) Inaction-Plant Size Elasticity (b) Job Creation Rate



Note: Panel (a) plot shows coefficients and 95% confidence intervals 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 industry-year and state-year fixed effects. Panel (b) shows job creation rates by size bin over time (relative to 1994), defined as the positive employment change in each size bin divided by the average aggregate employment across both start and end years. 1995 and 1997 are omitted due to large spikes in those years (one positive and negative, so no substantive impact on the trend in the pre-period).

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 the last three rows in Table 3 (even columns). A firm is less likely to be in the inaction range, the job creation rate is higher, and is more likely to add new products to their output portfolio when it has contract workers on their rolls.[27]

The remaining analysis in this section links 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. We construct Bartik-style instruments for growth in manufacturing employment and run regressions of the form:

$$g_d = \beta_0 + \beta_1 \widehat{g}_d + \beta_2 \text{Contract Init}_d + \beta_3 \widehat{g}_d \cdot \text{Contract Init}_d + \gamma_s + \epsilon_d$$

Here $g_d \equiv (L_{d,t+k} - L_{dt})/L_{dt}$ is the growth rate of manufacturing employment in district d between dates t (1997-1999) and $t+k$ (2007-2009), Contract Init$_d$ is the share of manufacturing firms using contract workers in the initial period (1997-1999), $\widehat{g}_d \equiv (\widehat{L}_{d,t+k} - L_{dt})/L_{dt}$ is the predicted growth rate in employment in the district and γ_s are state fixed effects.[28] To measure predicted employment growth

[27] The job creation rate is defined as the employment change for firms that increase employment divided by the average of the firm's employment at the beginning and end of the period.

[28] The ASI only provides district identifiers until 2009. We pool years into a pre- and post-period to increase precision.

in a district, we start by computing 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 $\hat{L}_{d,t+k}$ by multiplying initial district employment by the predicted growth rate.[29] The 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 good predictive power.

[29]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.

Table 4: Contract Labor and Responsiveness to Local Bartik Labor Demand Shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Predicted Emp Growth	0.783***	0.842***	0.959***	0.982***							
	(0.130)	(0.150)	(0.121)	(0.145)							
Initial Contract Measure			-0.079	-0.060	-0.083	-0.070	-0.092	-0.109	-0.059	-0.038	-0.031
			(0.078)	(0.073)	(0.087)	(0.076)	(0.071)	(0.079)	(0.083)	(0.094)	(0.088)
Predicted Emp Growth Initial Contract Measure			0.434**	0.428**	0.628**	0.622***	0.639***	0.655***	0.566***	0.440*	0.472*
			(0.216)	(0.194)	(0.263)	(0.222)	(0.207)	(0.164)	(0.165)	(0.258)	(0.243)
Pro-Worker State × Initial Contract Measure										-0.200	-0.197
										(0.152)	(0.139)
Predicted Emp Growth × Pro-Worker State × Initial Contract Measure										0.962*	0.801*
										(0.509)	(0.468)
R^2	0.51	0.49	0.53	0.52	0.56	0.60	0.65	0.60	0.62	0.57	0.60
N	385	358	385	358	380	358	358	380	358	380	358
F-Stat	36.41	31.56									
State FE	X	X	X	X	X	X	X	X	X	X	X
District Controls		X		X		X			X		X
State FE X Pred. Emp Growth					X	X	X	X	X	X	X
District Cont. X Pred. Emp Growth							X				
Staffing Measure								X	X		

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 districtâs 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

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 during the 2000s. 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 .43 (columns 3 and 4, where the latter controls for district level conditions in 1990). Columns 5 and 6 show that this result strengthens as we allow 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 does not appear to simply pick 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 (as computed in Section 4.2) as an alternative measure of access to staffing employment. We obtain qualitatively similar results. 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.

Table 5 moves the analysis back to the firm-year panel and uses annual rainfall in a district as an alternative economic shock. The variable "shock" in Table 5 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 2010, -1 if rainfall in the firm's district in that year is above the 80th percentile in the district's distribution, and 0 otherwise.[30] 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.

[30]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. Recall the ASI only provides districts until the 2009-2010 fiscal year, hence we only consider rainfall data until 2010.

Table 5: Rainfall Shock Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Shock	0.004	0.005	0.003	0.001	-0.035**	-0.005
	(0.006)	(0.004)	(0.006)	(0.006)	(0.017)	(0.008)
Shock X Post	-0.004		0.003	0.003	0.065***	0.002
	(0.008)		(0.008)	(0.008)	(0.023)	(0.009)
Contract		0.479***	0.388***			
		(0.016)	(0.015)			
Shock X Contract		-0.013*	0.009			
		(0.007)	(0.012)			
Contract X Post			0.140***			
			(0.017)			
Shock X Contract X Post			-0.036**			
			(0.016)			
Large				1.129***		
				(0.019)		
Large X Post				0.140***		
				(0.013)		
Shock X Large				0.012		
				(0.009)		
Shock X Large X Post				-0.035***		
				(0.010)		
Staffing X Post					0.028***	
					(0.009)	
Shock X Staffing					0.013**	
					(0.005)	
Shock X Staffing X Post					-0.021***	
					(0.007)	
Shock X ProWorker						0.030**
						(0.015)
Shock X ProWorker X Post						-0.036*
						(0.019)

Note: Observations at the firm-year level. Outcome is log non-managerial employment. Post is a dummy for after 2001. (Negative) 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 districtâs distribution, -1 when above the 80th percentile and 0 otherwise. Contract is a dummy for whether the firm hires more than 50% of workers through contract labor. Large is a dummy for whether the firm has more than 100 workers. Staffing is the log 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. All regressions include firm fixed effects, state-year fixed effects, industry-year fixed effects and district condition-year fixed effects. District conditions include (all measured in 1990) the difference in log value-added per worker 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.* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

The patterns in Table 5 are consistent with the view that the use of contract labor 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 50 percent of more of their workers hired under contract (column 2) and this is particularly true post-SAIL (column 3; in fact, the post-SAIL period explains all of the effect in column 2). 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.

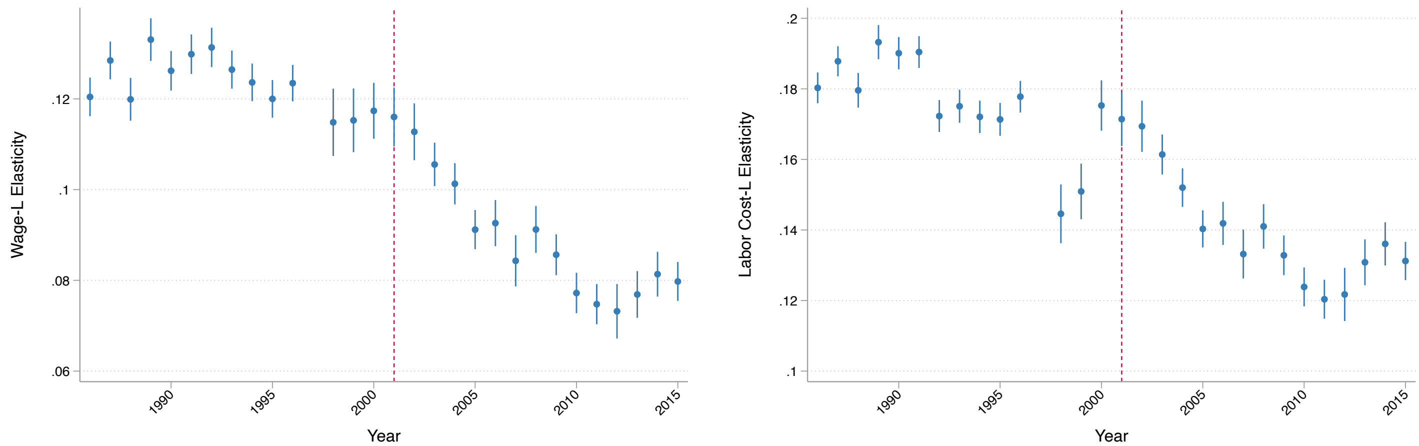
We start in panel (a) of Figure 9 by plotting the elasticity of average wages with respect to total non-managerial employment over time. The average wage is defined as the total wage bill for non-managerial workers divided by the number of workers.[31] As before, we first regress log average wage on log employment interacted with year dummies, as well as a full set of industry-year dummies and reports in the figure coefficients on log employment for each year. There is a positive elasticity of the average wage 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 2013-2015. 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)

[31] The results are unchanged if we measure the average daily wage rather than the average wage per worker.

from 1985 to 2001 of about .18, and this elasticity starts sharply declining in 2002, reaching .13 by the end of the sample period.

Figure 9: Labor Cost and Plant Size Over Time

(a) Wage-Plant Size Elasticity (b) Labor Cost-Plant Size Elasticity



Note: Figures plot coefficients and 95% confidence intervals 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.

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 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 workers when firms recruit contract labor, which would tend to exaggerate the drop in labor cost associated with the rise of the contract labor system.

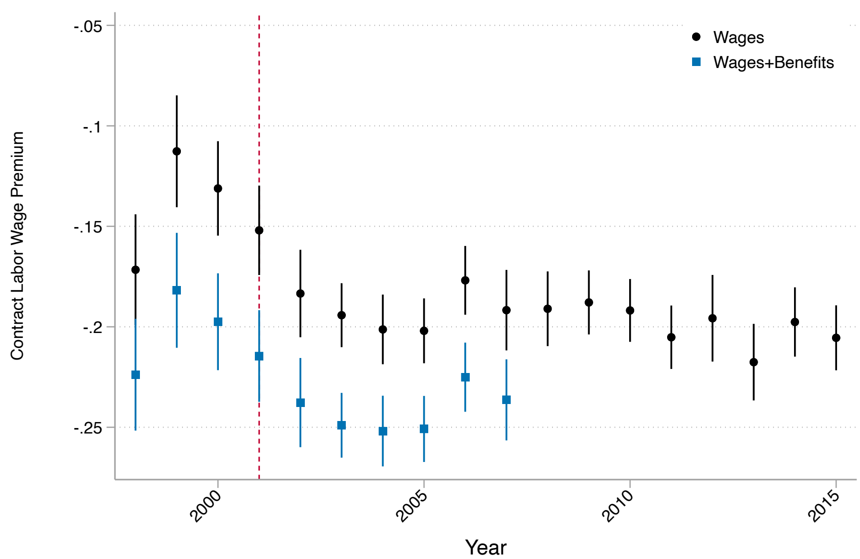
Ideally, we would like to estimate the difference in cost per effective unit of labor between contract and permanent workers, as well as also assess how this difference in cost varies by firm size. Since the ASI has no information on worker characteristics, we instead look at the contract workers relative wage holding constant the composition of employment within the firm in a flexible fashion. For each type of labor $\ell \in \{\text{Contract}, \text{Permanent}\}$ we run the following specification for firm i in year t:

$$\ln W_{\ell itb} = \gamma_{ktb} + \beta_t \mathbb{I}\left\{\ell = \text{Contract}\right\} + \epsilon_{it}$$

where $W_{\ell it}$ is the average daily wage of type-ℓ workers, γ_{ktb} are industry-year-bin fixed effects. Here, b indicate which group of the share of contract workers firm i falls into year t. We bin the contract labor share into five groups depending on whether the firm employs no contract workers, between 0-24%, 25-49%, 50-74%, or 75-100% of workers through contracting. 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 10 plots the estimates of β_t which identifies 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.[32] Contract workers are about 20% cheaper than full-time workers in terms of wages, and about 25% cheaper in terms of overall payments. After some swings in the late 1990s and early 2000s, these wage and labor cost differences remain quite stable across the 2000s.

Figure 10: Relative Cost of Contract Labor



Note: Figures plot coefficients and 95% confidence intervals 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 benefits. Wages and benefits are only provided separately by type of worker from 1998 to 2007.

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 11 we plot the raw non-parametric relationship between the relative wage of contract workers and non-managerial employment in 2000 and 2015. 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. Con-

[32]Recall wages for full-time and contract workers are separately provided between 1998 and 2015; while the same is true for bonuses and benefits between 1998 and 2007.

sider 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 multiple times before, data limitations do not allow us to 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 2015 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 estimating the following regression:

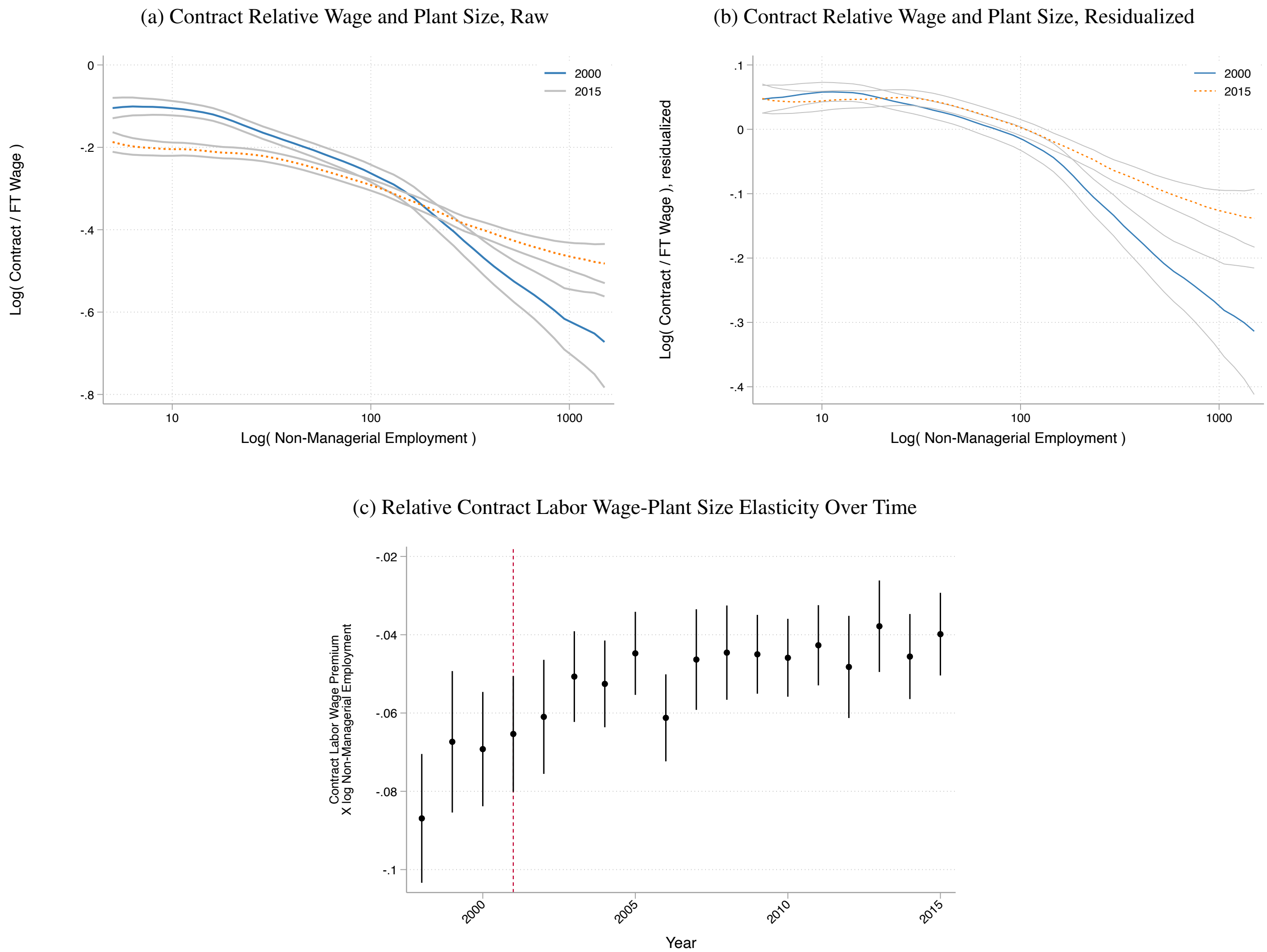
$$\ln W_{\ell itb} = \gamma_{ktb} + \beta_{1t}\mathbb{I}\left\{\ell = \text{Contract}\right\} + \beta_{2t}\ln L_{it} + \beta_t^{Size}\mathbb{I}\left\{\ell = \text{Contract}\right\} \times \ln L_{it} + \epsilon_{it}$$

where L_{it} is the number of non-managerial workers. The coefficients β_t^{Size} 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 11 plots these coefficients. While our data only allow us to examine this relationship from 1998 onwards, it appears that the fall in the wage premia of full-time workers within large plants began around or just after the SAIL adjudication.

Figure 11 suggests that the cost of full-time workers relative to contractors is falling for larger plants during the 2000s. In Figure 12, 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 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 10 suggests the full-time wage elasticity was likely constant prior to 1998 given the dominance of full-time vis-a-vis contract workers during

Figure 11: Contract and Full-Time Relative Wages and Plant Size Over Time



(a) Contract Relative Wage and Plant Size, Raw

(b) Contract Relative Wage and Plant Size, Residualized

(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 and 95% confidence intervals on the contract X year X log non-managerial employment.

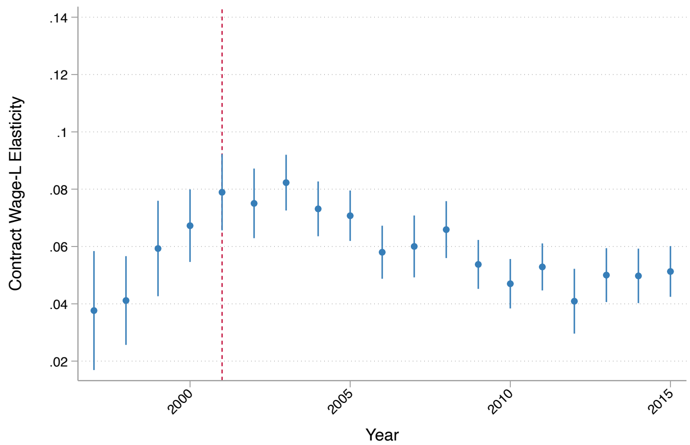
those early years.

Overall, panels (a) and (b) of Figure 12 suggest that the rise in the relative cost of contract workers amongst large plants documented in Figure 11 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.

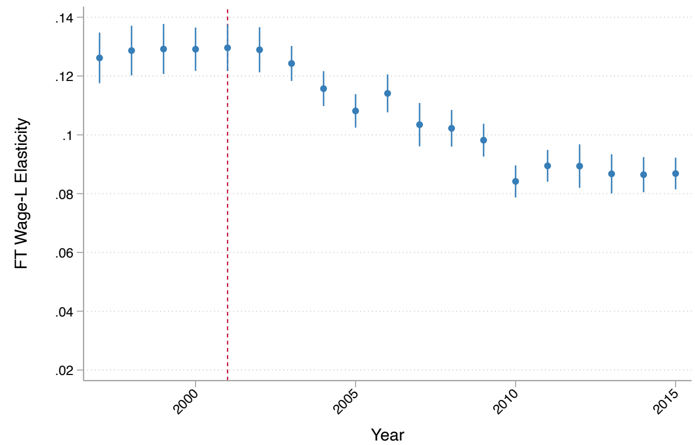
Panel (c) in Figure 12 examines how the relationship between the elasticity of full-time wages to non-managerial employment and a district's level of staffing in 1990 evolved over time. If the SAIL

Figure 12: Contract and Full-Time Wages and Plant Size Over Time

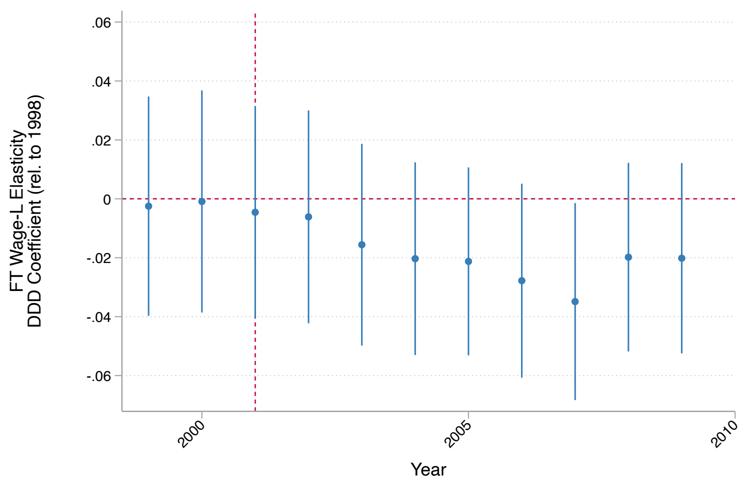
(a) Contract Wage - Contract Employment Elasticity Over Time



(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 along with the 95% confidence intervals. 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 (and the corresponding 95% confidence intervals from standard errors clustered at the district-year level) 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. District identifiers are not provided after 2009, so panel (c) ends then.

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 downward trend in these coefficients post-2001.

6 A Model of Firm Growth, Innovation, and Firing Costs

We now develop a model of innovation by heterogeneous firms to quantify the effect of contract labor in the presence of the IDA on aggregate TFP. The model is designed to capture two of our central facts: the gap in labor productivity between large and small firms and the decline of this gap over time, and the use of contract employment by large firms. The goal then is quantify the effect of the increased use of contract labor on the gap in labor productivity between large and small firms and on aggregate TFP. The model accounts for contract labor's static impacts on TFP that accrue through changes in misallocation, as well as the dynamic impacts on productivity growth through firms' innovation decisions (which we also document in the data). Due to our focus on the aggregate impacts of contract labor on the Indian economy, the model does not take into account the evidence shown earlier that contract labor also lowers the wages of permanent workers.[33]

The model builds on Klette and Kortum (2004) where we distinguish between two types of firms: a one with a low propensity to innovate and that can retrench workers without any costs, and another with high propensities to innovate that faces firing costs when they retrench workers. The anticipation of future retrenchment costs cause innovative firms to hire a sub-optimally low number of workers and to invest less in innovation. The model calibrates these retrenchment costs from the positive relationship between the firm's labor productivity and size in the cross-section. Firms subject to the IDA can circumvent the adjustment costs by hiring contract workers after paying a fixed cost. We infer the change in this fixed cost by the increased use of contract labor by large firms after the early 2000s. We then use model to quantify the effect of the increased use of contract labor on the sub-optimal use of labor by large firms (i.e. static misallocation) and the innovation rate.

[33]An extension of the model in which full-time and contract workers are treated as distinct labor types aggregated by firms' production functions would permit an analysis of these distributional impacts. This would also account for the impacts on relative wages we document, as demand (and hence wages) for full-time workers would fall as the cost of hiring contract workers decreases. Yet other aspects of contract labor's distributional consequences, e.g. job security, would be harder to capture parsimoniously and affirms our focus on aggregate impacts. We discuss the likely impact of these effects on our results at the end of this section.

6.1 Static Equilibrium

Aggregate output is a CES combination of varieties:

$$Y = \left(\int_0^1 (q_j y_j)^{\frac{\sigma-1}{\sigma}} \, dj \right)^{\frac{\sigma}{\sigma-1}}$$

where y_j denotes the quantity and q_j the quality of variety j. Output of a variety is given by $y_j = \ell_j$ where ℓ_j denotes the number of workers used to produce variety j. A worker can be full-time (employed directly by the firm) or a contract worker (employed via a staffing company). The two types of workers are perfect substitutes in production and are paid the same wage w.

To capture the size dependent firing restriction, we assume that a blueprint for a product is owned by two types of firms, a "high-type" and a "low-type" firm where the latter is more innovative than the former. In addition, to capture the effect of the IDA, we assume that the high-type firm faces firing costs while the low-type firm does not. A high-type firm has to pay κw for every full time worker it wishes to fire, whereas a "low-type" firm can fire its full-time workers with no cost. These two assumptions imply that high-type firms will be larger than low-type firms, which captures the fact that large firms face firing costs while small firms do not.[34] Finally, we assume contract workers can be fired at zero cost (by all firms) but an employer needs to pay a fixed cost F (in units of the output good) for each product line they are employed on. This last assumption generates the fact that large firms are more likely to hire contract workers.

Given the fixed cost of employing contract workers, a low-type firm will always employ full-time workers. Employment and revenue per worker of variety j of such firms is given by:

$$\begin{aligned} \ell_j &= \left(\frac{\sigma - 1}{\sigma} \right)^{\sigma-1} L \, w^{1-\sigma} q_j^{\sigma-1} \\ \frac{p_j \, y_j}{\ell_j} &= \left(\frac{\sigma}{\sigma - 1} \right) w \end{aligned}$$

where L is aggregate labor supply. Employment is a power function of the quality of the variety and labor productivity is proportional to the aggregate wage (and same for all varieties owned by low-type firms).

A high-type firm may choose to employ full time workers on some product lines and contract

[34] If we instead assume that firing costs depend on the total employment of a firm, the model quickly becomes intractable. In Klette and Kortum-style models of firm dynamics, tractability is typically attained by ensuring firm behaviour can be separated into a series of independent product-level decisions. Value functions and optimal choices can then be characterized product by product. Firing costs that depend on firm-level employment introduce an interdependence between choices on different product lines (since employment on each line affects total employment, and can therefore affect the firing costs faced on other products). The model no longer admits a clean analytical solution. Instead, we assume firing costs are type-dependent so they no longer depend on choices made on individual products. In equilibrium, our model still yields large firms facing firing costs as it is the high-type firms who both innovate to become large while also facing these adjustment costs.

workers on other product lines. The critical variable is the probability that the firm will be forced to retrench when another firm innovates on its products, which occurs with probability x (which we endogenize later). If the high-type firm chooses to employ full time workers on a product line, it faces an additional labor cost $x\,\kappa\,w\,\ell$ due to the possibility that it will have to close that product line because of innovation by another firm. Conditional on employing full time workers, profit-maximizing employment and labor productivity are therefore given by:

$$\begin{aligned}
\ell_j &= \left(\frac{\sigma-1}{\sigma}\right) L\,w^{1-\sigma}\,(1+x\,\kappa)^{-\sigma}\,q_j^{\sigma-1} \\
\frac{p_j\,y_j}{\ell_j} &= \left(\frac{\sigma}{\sigma-1}\right) w\,(1+x\,\kappa)
\end{aligned}$$

Firing costs results in lower employment and *higher* average product of labor on the product lines of high type firms that employ full time workers. The higher average product of labor reflects the higher marginal cost of full time workers due to the expected firing cost.

A high-type firm can avoid the retrenchment cost by paying a fixed cost F to employ contract workers. In this case, profit maximizing employment and labor productivity are given by equation 6.1. It will choose to do this when the flexibility gains from employing contract labor relative to full time workers exceeds the fixed cost F, which is the case when q_j exceeds the threshold quality q^* defined as:

$$q^* \equiv \frac{\sigma}{\sigma-1} w \left[1-(1+x\kappa)^{1-\sigma}\right]^{\frac{1}{1-\sigma}} (\sigma F)^{\frac{1}{\sigma-1}}.$$

The threshold quality q^* grows with the wage w and is increasing in the fixed cost of using contract labor F.

Finally, after imposing the aggregate labor market clearing condition, the wage is proportional to aggregate output per worker $\frac{Y}{L}$ given by:

$$w \propto \frac{Y}{L} = \left(\int_0^1 \left(\frac{q_j}{1+x\kappa\mathbb{I}_j}\right)^{\sigma-1} dj\right)^{\frac{1}{\sigma-1}}$$

where $\mathbb{I}_j$ is an indicator variable for a product staffed by full-time workers owned by a high-type firm. Firing costs lower aggregate output per worker because they result in more dispersion in labor productivity across firms. The availability of contract workers increases aggregate TFP by lowering the share of products of high-type firms that are subject to firing costs.

6.2 Innovation

We now endogenize the innovation rate x as a function of the cost and benefit of innovation. Time is continuous and we omit time subscripts when possible. When a firm successfully innovates, it improves upon the quality of a randomly chosen product with step-size λ, where the step-size follows a Pareto distribution with unit scale and shape parameter θ. The cost of innovation (in units of the final good) per product owned by a firm is:

$$c_H(x_H) = \left(\frac{x_H}{\xi_H}\right)^{\frac{1}{1-\beta}} Y$$

where x_H is the flow rate of innovation per product owned by a high-type firm and ξ_H is the productivity of the high-type firm in R&D. The cost of innovation for the low-type firm is given by a similar expression, with x_H and ξ_H replaced by x_L and ξ_L. Note that the arrival rate of new products of a firm is in proportion to the number of products owned by a firm. For example, a firm with two products is twice as likely to innovate on another firm's variety compared to a firm with one product.

The marginal private benefit of resources spent on innovation is the product of the marginal increase in innovation from additional R&D and the expected value of a variety obtained through innovation. Equating the marginal cost with the marginal benefit of the innovation, the optimal innovation rate of the high-type firm x_H is:

$$x_H = \tilde{\beta}\, \xi_H^{1/\beta}\, \mathbb{E}\left[v_H\left(\lambda \hat{q}_j\right)\right]^{\frac{1-\beta}{\beta}} \tag{1}$$

where v_H is the the value of a variety for a high-type firms normalized by aggregate output per worker, and $\hat{q}_j$ is the quality of a product q_i normalized by aggregate output per worker.[35] The optimal innovation rate for a low-type firm x_L is given by the same expression with v_H replaced by v_L. Equation 1 says that the innovation rate is increasing in the productivity in R&D ξ and the expected value of a variety. Holding the expected value of a variety constant, $\xi_H > \xi_L$ implies that the innovation rate of high-type firms is higher than that of low-type firms.

Turning to entrants, a unit mass of entrants are created every period with a cost of innovation given by $(x_E/\xi_E)^{\frac{1}{1-\beta}}\, Y$ where x_E denotes the innovation intensity of an entrant. The type of an entrant (high or low type) is realized after they invest in R&D, where $\alpha \leq 1$ denotes the ex-ante probability an entrant is a high type firm. The expected return to innovation for an entrant is a weighted average of the value of a product for a high- and a low-type firm. Equating the cost to the benefit, the optimal innovation rate for an entrant is given by:

$$x_E = \tilde{\beta}\xi_E^{1/\beta}\left\{\, \alpha\mathbb{E}\left[v_H\left(\lambda\hat{q}\right)\right] + (1-\alpha)\mathbb{E}\left[v_L\left(\lambda\hat{q}\right)\right] \right\}^{\frac{1-\beta}{\beta}}. \tag{2}$$

The innovation rate of entrants is increasing in the productivity of entrants in R&D and in the

[35] And $\tilde{\beta} \equiv (1-\beta)^{\frac{1-\beta}{\beta}}$.

weighted average of the value of a variety for a high- and low-type firm.

The key endogenous variables in the innovation rates in equations 1 and 2 are the expected value of a variety for high- and low-type firms. For a low-type firm, the expected value of a variety is given by a standard arbitrage equation:

$$\mathbb{E}\left[v_L\left(\hat{q}\right)\right] = \frac{\sigma^{-1}\,\mathbb{E}\left[\hat{q}^{\sigma-1}\right]}{\rho + x + \left(\sigma-1\right)g} + \frac{\beta\tilde{\beta}\xi_L}{\rho+x}\mathbb{E}\left[v_L\left(\lambda\hat{q}\right)\right]^{1/\beta}$$

where g and x denote the growth rate and the innovation rate. The first term is the expected value of the flow of profits from owning a variety. The second term measures the value from innovating and possibly grabbing another variety.

For a high-type firm, the expected value of a variety v_H is given by a similar arbitrage condition:

$$\begin{aligned}\mathbb{E}\left[v_H\left(\hat{q}\right)\right] = &\frac{\mathbb{P}\left(\hat{q}<\hat{q}^*\right)\left(1+x\kappa\right)^{1-\sigma}\mathbb{E}\left[\hat{q}^{\sigma-1}|\,\hat{q}<\hat{q}^*\right] + \mathbb{P}\left(\hat{q}>\hat{q}^*\right)\left(\mathbb{E}\left[\hat{q}^{\sigma-1}|\,\hat{q}>\hat{q}^*\right] + \mathbb{E}\left[e^{-(r-g+x)\tilde{t}(\hat{q})}|\,\hat{q}>\hat{q}^*\right]\varepsilon\right)}{\sigma(\rho+x+(\sigma-1)g)}\\ &-\mathbb{P}\left(\hat{q}>\hat{q}^*\right)\frac{F}{\rho+x}\\ &+\frac{\beta\tilde{\beta}\xi_H}{\rho+x}\mathbb{E}\left[v_H\left(\lambda\hat{q}\right)\right]^{1/\beta}\end{aligned}$$

where $\mathbb{P}(\hat{q}>\hat{q}^*)$ denotes the probability that the normalized quality of the innovated variety exceeds the threshold quality normalized by aggregate output per worker, $\tilde{t}\left(\hat{q}\right) = g^{-1}\left[\ln(\hat{q}) - \ln(\hat{q}^*)\right]$ denotes the duration for which the normalized quality of the innovated variety remains above the normalized threshold quality.[36]

The expected value of a variety for a high type firm can be interpreted as follows. The first line is the expected flow profits from owning a variety. Since $(1+x\kappa)^{1-\sigma} < 1$, the value of a product of a given quality is lower for a high type firm because of the possibility it will be forced to hire too few full time workers due to the firing cost. The value is adjusted for the length of time $\tilde{t}$ the firm expects to hire contract labor conditional on drawing a productivity initial above the cutoff $\hat{q}^*$. The second term is the fixed cost paid if the product is of high enough quality to employ contract workers. The third term is the expected gain from innovation.

The share of products owned by the two types of firms and the aggregate rate of innovation is then pinned down by the rates of innovation. Specifically, the share of products owned by high type firms ϕ in a steady state is:

$$\phi = \frac{(x_H - x_L - x_E) + \sqrt{(x_H - x_L - x_E)^2 + 4(x_H - x_L)\alpha}}{2(x_H - x_L)}.$$

[36] And $\varepsilon \equiv \frac{1}{\sigma}\frac{(1+x\kappa)^{1-\sigma}-1}{[\rho+x+(\sigma-1)g]}\hat{q}^* + \frac{F}{\rho+x}$.

The steady state share of high-type firms is increasing in x_H and decreasing in x_L. The aggregate rate of innovation is then given by the innovation rates and the shares of the three types of firms:

$$x = \phi\, x_H + (1-\phi)\, x_L + x_E$$

where the innovation rates of each type of firm are given by equations 1 and 2. To get a stationary quality distribution, we add a reflecting barrier where the bottom ψ percent of products draw new qualities from $j \in [\psi, 1]$ and the quality of the top ψ percent of products is not upgraded. The expected growth rate of aggregate output Y is then given:

$$g = \frac{1}{1-\psi}\left(x \cdot \frac{1}{\theta - (\sigma - 1)}\right) \tag{3}$$

where the average step size $\frac{1}{\theta-(\sigma-1)}$ is a function of the shape parameter of the quality draw distribution θ and the elasticity of substitution σ.

6.3 Parameter Estimates

The model is characterized by 11 parameters: $\{\rho, \sigma, \beta, \psi, \alpha, \kappa, \xi_H, \xi_L, \xi_E, \theta, F\}$. We impose values for ρ, β, ψ, and σ shown in the bottom panel in Table 7.[37] We estimate the remaining parameters $\{\alpha, \kappa, \xi_H, \xi_L, \xi_E, \theta, F\}$ in three steps.

First, we treat the innovation rates as exogenous and estimate $\{x_H, x_L, x_E, \alpha, \kappa, F, \theta\}$ to match the moments in the period prior to 2000 (the "pre-period") shown in Table 6. The innovation rates for high- and low-type firms x_H and x_L are jointly identified by the job creation rate by incumbents and the 75th percentile of the firm age distribution. The incumbent job creation rate identifies total innovation by incumbents $x_H + x_L$, since greater innovation by all incumbents increases the rate they add products and, in turn, job creation by incumbent firms. The 75th percentile of the firm age distribution pins down the ratio of x_H to x_L since a smaller gap between x_L and x_H implies that the two types of firms are more similar and the dispersion in age is smaller. Innovation by entrants x_E is identified by the share of total employment by entrants. The more innovative are entrants, the more product lines they hold and the higher their share of overall employment. To identify the firing costs and contract labor adoption costs, we target the elasticity of value-added per worker with respect to firm employment and the share of large firms using contract labor intensively.[38] Since the ratio of average revenue products of labor between firms employing and not employing contract labor is

[37] We pick β to match the elasticity of successful innovation with respect to R&D. See Acemoglu et. al. 2018 and references therein for the elasticity of innovation with respect to R&D resources. We explore robustness to alternative parameter values to these four exogenously calibrated parameters in section E in the appendix.

[38] To account for differences in labor quality across firms, we measure *quality-adjusted* employment of the firm as the wage-bill. We provide detailed descriptions of how each data moment is computed in the notes to Table 6.

$1 + x\kappa$ in the model, the former identifies κ given a value of x pinned down by the innovation rates x_H, x_L, and x_E. The latter identifies the fixed cost of hiring contract workers, since this parameter determines the extensive margin of how many firms adopt contract labor. The share of high type firms among entrants α is pinned down by the difference in exit rates between young and old firms conditional on firm size. Due to selection, the pool of older firms will contain more high-type firms, and so a higher α manifests itself through more high-type firms amongst old firms and a larger gap in exit rates. Lastly, the shape parameter θ of the distribution of innovation draws is set to match the growth rate conditional on x as shown in equation 3.[39]

Table 6: Moments in the Model and Data

Moments	Parameter Identified	Period	Data	Model
Rate of Job Creation by Incumbents[1]	$x_H + x_L$	Pre	0.0434	0.0526
Share of Employments in Entrants[2]	x_E	Pre	0.0456	0.0365
Difference in Exit Rates, Young vs. Old[3]	α	Pre	0.0132	0.0134
VA/Wage-Bill vs Wage-Bill Elasticity[4]	κ	Pre	0.0444	0.0408
Pre-Period, % Large Firms with Intensive Contract Labor Use[5]	F^{Pre}	Pre	0.2175	0.2168
Post-Period, % Large Firms with Intensive Contract Labor Use[5]	F^{Post}	Post	0.3575	0.3597
75th Percentile of Firm Age	x_H/x_L	Pre	21.00	15.95
TFP Growth[6]	θ	Pre	1.0740	1.0695

[1] Job creation by incumbents is sum over incumbent firms with increasing employment in each one-year period divided by the average of employment in the initial and final year.
[2] Share of employment of entrants in year t is employment of establishments in year t that did not exist in year t-1 as a share of total employment in year t.
[3] Young firms are those with age < 10 and old firms are those with age > 10. The exit rate for young vs. old firms is computed by regressing an indicator variable for exit over one year dummies for young and old, firm employment), and state-year and industry-year fixed effects.
[4] The VA/Wage-Bill vs Wage-Bill elasticity is computed by regressing log VA/Wage-Bill on log Wage-Bill. This measures the average product of labor vs size elasticity, measuring labor inputs using the wage bill rather than the number of workers (to account for differences in worker skill). This elasticity is smaller than the VA/worker elasticity (around 0.03 vs 0.1), but both display similar percentage falls using the 2000s (Figures 5 and B.1). The model is better able to fit this smaller value jointly with the observed job creation rates (too high an VA/worker decreases innovation by incumbents to implausibly low levels).
[5] Intensive contract labor use defined as hiring more than 50% of workers through contractors. Large defined as more than 100 workers.
[6] TFP growth for manufacturing plants over 1993-2007, taken from Bollard, Klenow, and Sharma (2013).
Note: The pre-period and post-period moments are averages over 1999-2001 and 2013-2015 respectively, unless otherwise noted, and includes establishments with more than 5 workers.

The top panel in Table 7 shows the values of $\{x_H, x_L, x_E, \alpha, \kappa, F, \theta\}$ that most closely match these moments. High-type firms are much more innovative than low-type firms (who conduct almost no innovation) and about 6.3 times as innovative as entrants. There are many more low-type firms than

[39] We minimize the weighted sum of squared percentage deviations of the model-generated moments from the data moments, where the weights on the TFP growth and intensive contract labor usage are five times the weights on other moments.

high-type firms in the economy, with only around 2.6% of entrants likely to be high-type. This is around the value of 11% that Akcigit, Alp and Peters (2021) find in the same context. Firing costs κ are estimated to be around 6.9 times the wage rate, while the cost of adopting contract labor F is around 1.2 units of the final good. A shape parameter θ for the distribution of the quality draws of around 3 is needed to match the aggregate growth rate.

Table 7: Estimates of Model Parameters

Parameters	Description	Estimate
Pre-Period (Step 1)		
x_H	Innovation rate for high-type incumbents	0.1203
x_L	Innovation rate for low-type incumbents	0.0000
x_E	Innovation rate for entrants	0.0191
α	Proportion of high-type firms among entrants	0.0255
κ	Firing cost of full-time labor	6.9007
F	Fixed cost of adopting contract labor, Pre period	1.2119
θ	Shape parameter of Pareto distribution	2.9953
Pre-Period (Step 2)		
ξ_H	Innovation parameter for high-type incumbents	0.2516
ξ_L	Innovation parameter for low-type incumbents	0.0027
ξ_E	Innovation parameter for entrants	0.0954
Post-Period (Step 3)		
F	Fixed cost of adopting contract labor, Post period	0.6489
Externally Calibrated		
σ	Elasticity of Substitution	2.00
ρ	Discount rate	0.05
β	Elasticity of successful innovation	0.50
ψ	Parameter for Reflecting Barrier	0.02

In the second step, we invert the expressions for optimal innovation decisions (given by equation 1 for incumbents and by equation 2 for entrants) to recover the productivity parameters in the R&D sector ξ_H, ξ_L, and ξ_E from the innovation rates x_H, x_L, and x_E shown in the top panel of Table 7. The second panel in Table 7 shows the resulting productivity parameters in R&D of the high-type and low-type firms as well as the entrants. The productivity of high-type firms in R&D is about 2.6 times higher than the productivity of entrants and 93 times larger than the productivity of low-type firms in R&D.

The third step is to estimate the change in fixed cost F necessary to explain the change in the share of large firms that use contract labor intensively after 2000. Specifically, in the post-period we assume that $\rho, \sigma, \beta, \alpha, \kappa, \xi_H, \xi_L, \xi_E, \theta$ remain fixed (at the values shown in the top two panels in Table 7) and choose the change in F that most closely matches the share of large firms adopting intensive use of contract labor observed by the end of the 2000s.[40] This is shown in the third panel in Table 7. To "explain" an increase from 22% to 36% in the share of labor firms that use contract labor intensively, the fixed cost of employing contract labor must have fallen from 1.21 to 0.65 in units of the final good over this period.

6.4 Quantifying the Impacts of Contract Labor Growth

How did the proliferation of contract labor reshape Indian manufacturing during the 2000s? The idea of the third step in Table 7 is to answer this question. By holding all model parameters fixed at their values estimated to match moments in 2000, and varying only the fixed cost of hiring contract workers to match its increased using amongst large firms by 2015, this counterfactual allows us to quantify what Indian manufacturing would look like had only this change occurred over the fifteen year period. In turn, it illuminates how much of the aggregate patterns we document can be explained by the increased use of contract labor alone.

Table 8 shows the effect of the estimated fall in the fixed cost of hiring contract workers on the elasticity of value-added per worker with respect to size, the employment share of entrants, and the job creation rate of incumbent firms. None of these moments are targeted in estimation, so there is no reason to expect the model to necessarily fit these empirical patterns.

Table 8: Simulating the Impact of the fall in Contract Labor Adoption Costs

	Data		Model		%Δ Pre to Post	
Moments	Pre	Post	Pre	Post	Data	Model
VA/Wage-Bill vs Wage-Bill Elasticity	0.0444	0.0222	0.0408	0.0180	-49.98%	-55.83%
Share of Employments in Entrants	0.0456	0.0405	0.0365	0.0303	-11.09%	-17.03%
Rate of Job Creation by Incumbents	0.0434	0.0693	0.0526	0.0492	59.76%	-6.58%

Note: The first and second columns reproduce the data and model-generated moments for the pre-period from Table 6. The third and fourth columns present the data and model-generated moments for the post-period, where the model-generated values are based on the estimated fall in F presented in Table 7. The fifth and sixth columns compare the percentage change in the data and model-generated moments from the pre- to post-period.

Row 1 in Table 8 shows how the reduction in the fixed cost of using contract labor affects the average product of labor size elasticity. The model predicts that as more large, high-type firms hire contract labor in response to lower adoption costs, the relationship between average product of labor and firm size flattens by around 56%. This is close to the reduction of 50% observed in the data during the 2000s. In other words, the increased use of contract labor can explain the entire fall in the difference in the average product of labor between large and small firms in the data.

[40] The simulation algorithm is detailed in Section D in the appendix.

Row 2 in Table 8 shows the effect of the expansion of the use of contract workers on the job creation rate of entrants. The model predicts that the employment share or job creation of entrants falls by 17% in response to lower contract labor adoption costs. This occurs since the value of entry has fallen. As more high-type firms adopt contract labor, they face lower expected retrenchment costs, receive a higher return to owning a product, and thus increase their rate of innovation. The value of low-type firms falls as their products are more likely to be stolen and the real wage rises due to increased labor demand by high-type firms. Since entrants expect to enter as low-type firms (due to the low value of α), the entry rate declines. Again, this is not too far from the 11% reduction in the employment share of entrants observed in the data.

The last row in Table 8 shows the effect on job creation by incumbents. In the data job creation by incumbents rises by about 60% during the 2000s. Our model delivers a decline by 7%. Table 9 shows why. The reduction in expected labor costs for large, high-type firms causes their distribution to fan out with the largest firms growing disproportionately as they accumulate new products (first row). As a result, more creative destruction takes place across products within firms rather than across firms. The second row shows product-level job creation in the model rises by 10% due to contract labor growth, still far short of the 60% increase in firm-level creative destruction observed in the data but now in the same direction.

Table 9: Size of High-type Firms and Product-Level Job Creation

	Pre	Post	Change
Ratio of 90/10 Percentiles of Size, High-type Firms	168.17	312.40	85.76%
Product-level Job Creation, due to Incumbent Innovation	0.0500	0.0547	9.52%

Note: The table presents i) the ratio of 90/10 percentiles of size (measured by employment) for high-type firms and ii) the product-line level job creation due to incumbent innovation, both generated by the model, in the respective period as well as the changes. The product-level job creation due to innovation is defined as the sum of changes in employment at product lines where incumbent firms innovated, normalized by the average employment across both periods. For each moment, the first column presents the value in the pre-period, the second that in the post-period, and the last the percent change over the two periods.

Table 10 shows the static gains in aggregate output and consumption due to the reduction in fixed cost of using contract workers. The first column shows that aggregate output (and TFP) increases by 7.6%, while the second column shows that aggregate consumption rises by 5.9%. The differences between output and consumption are resources spent on R&D and the fixed costs spent on employing contract workers. The static gain in aggregate output stems from better allocation of labor across products (and firms). Aggregate consumption increases by less than output because more of final outputs are spent on fixed cost of contract workers and R&D activities in the post-period than in the pre-period.

Table 10: Static Gains in Aggregate Output and Consumption

	Output	Consumption
Static Gains	7.60%	5.90%

Note: The table presents the static gains in aggregate output (first column) and consumption (second column) due to the estimated reduction in F between Pre- and Post-periods. (We ignore transitional dynamics.)

Another channel through which the reduction in fixed cost of contract labor may potentially affect output is through its impact on the long-run growth rate. However, its impact on the long-run TFP growth turns out to be almost zero in the estimated model; the aggregate innovation rate hardly changes from Pre-period to Post-period.[41] Table 11 shows why there is no increase in the aggregate innovation rate from the reduction in the cost of using contract labor. Specifically, the table shows the result of the following decomposition of the change in the aggregate innovation rate between the two steady states:

$$\Delta x = \Delta\left[\phi\, x_H\right] + \Delta\left[\left(1-\phi\right) x_L\right] + \Delta x_E. \tag{4}$$

The change in aggregate innovation rate can be decomposed as the sum of the change in high- and low-type innovation rates (weighted by their initial share of product lines) and the change in innovation by entrants.

The rise in innovation by high-type firms is almost exactly offset by a reduction in innovation by entrants, leaving the aggregate innovation rate (and hence the long-run growth rate) virtually unchanged. While large, high-type firms face a higher return to innovation as cheaper contract labor allows them to more easily circumvent the higher costs imposed by the IDA, entrants face stiffer competition by these expanding incumbents (since they are more likely to be low-type upon entry) and respond by innovating less. The reduction in innovation by entrants in the model leads to a prediction of a falling share of employment by entrants over the 2010s (see Table 8). Reassuringly, this is exactly what we observe in the data, despite this moment not being targeted by the model. Overall, our model therefore implies that all the productivity growth due to contract labor takes place one-time by reducing the level of static misallocation in the economy.

[41] As shown in equation (3), the % change in the growth rate is equal to % change in the aggregate innovation rate.

Table 11: Decomposing the Effect on Aggregate Innovation Rate

Period	x	High-type Innovation	Low-type Innovation	Entrant Innovation
Pre	12.32%	10.37%	0.00%	1.95%
Post	12.29%	10.50%	0.00%	1.79%
Change	-0.03%	0.13%	-0.00%	-0.16%

Note: The first column presents the aggregate innovation rate $x = \frac{1}{1-\psi}\left[\phi x_H + (1-\phi)x_L + x_E\right]$. The second to last columns decompose the aggregate innovation rate into each type of innovation (i.e. each additive term in the expression for x above).

7 Conclusion

We provide evidence that the employment restrictions on large Indian firms appears to have diminished since the early 2000s. 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 and a decrease in the average product of labor of large Indian firms. Our quantitative exercise suggests that the increased use of contract labor can "explain" the declining gap in the average product of labor, which accounts for 7.6% of the increase in aggregate TFP over this period.

The quantitative exercise also suggests that entrants will *lower* innovation because of the increased competition for large incumbent firms. In the data, this is consistent with a decline in the employment share of entrants. Furthermore the decline innovation among entrants entirely offsets the increased innovation by incumbents, so there is no net increase in innovation.

Despite the improvements seen in the data since the early 2000s, 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. This suggests that a greater reliance on contract labor is only a partial answer to the constraints faced by the formal manufacturing sector in India.

Finally, we did not address the distributional effects of contract employment. Our evidence suggests that the use of contract labor also lowers wages of permanent workers in the firms that employ these workers. The same force is likely to lower the wage gap between formal and informal workers in India. We also do not know the effects of employment as a contract worker on the worker themselves. In the absence of large-scale contract employment, how many of these workers would have become permanent workers and how many would have chosen to work in the informal sector? The distributional effect of contract employment depends on the magnitude of these forces, and it would be useful to quantify these margins in the future.

References

ABRAHAM, KATHARINE, AND ASHLEY AMAYA (2018), "Probing for Informal Work Activity," *NBER Working Paper 24880.*

ACEMOGLU, DARON, UFUK AKCIGIT, HARUN ALP, NICHOLAS BLOOM, AND WILLIAM KERR (2018), "Innovation, reallocation and growth," *American Economic Review*, 108(11): 3450-91.

ADHVARYU, ACHYUTA R., AND ANANT NYSHADHAM (2012), "Schooling, Child Labor, and the Returns to Healthcare in Tanzania," *Journal of Human Resources*, 47: 364-396.

AKCIGIT, UFUK, AND WILLIAM KERR (2018), "Growth through Heterogeneous Innovations," *Journal of Political Economy*, 126(4): 1374-1443.

AKCIGIT, UFUK, HARUN ALP AND MICHAEL PETERS (2021), "Lack of Selection and Limits to Delegation: Firm Dynamics in Developing Countries," *American Economic Review*, 111(1): 231â275.

AGHION, PHILIPPE, ROBIN BURGESS, STEPHEN REDDING, AND FABRIZIO ZILIBOTTI (2008), "The Unequal Effects of Liberalization: Evidence from Dismantling the License Raj in India," *American Economic Review*, 98(4): 1397-1412.

BESLEY, TIMOTHY, AND ROBIN BURGESS (2004), "Can Labor Regulation Hinder Economic Performance? Evidence from India," *Quarterly Journal of Economics*, 119(1): 91-134.

BOLLARD, ALBERT, PETER J. KLENOW, AND GUNJAN SHARMA (2013), "India's mysterious manufacturing Miracle," *Review of Economic Dynamics*, 16(1): 59-85.

CHAUREY, RITAM (2015), "Labor regulations and contract labor use: Evidence from Indian firms," *Journal of Development Economics*, 114(C): 224-232.

DRENIK, ANDRES, SIMON JÃGER, PASCUEL PLOTKIN, AND BENJAMIN SCHOEFER (2020),"Paying Outsourced Labor: Direct Evidence from Linked Temp Agency-Worker-Client Data," *Working Paper.*

DUBE, ARINDRAJIT, AND ETHAN KAPLAN (2010),"Does Outsourcing Reduce Wages in the Low-Wage Service Occupations? Evidence From Janitors and Guards," ILR Review, 63 (2):287â306.

DUTTA ROY, SUDIPTA (2004), "Employment dynamics in Indian industry: adjustment lags and the impact of job security regulations," *Journal of Development Economics*, 73(1): 233-256.

FALLON, PETER R, AND ROBERT E. B. LUCAS (1991), "The Impact of Changes in Job Security Regulations in India and Zimbabwe," *World Bank Economic Review*, 5(3): 395-413.

FALLON, PETER R, AND ROBERT E. B. LUCAS (1993), "Job security regulations and the dynamic demand for industrial labour in India and Zimbabwe," *Journal of Development Economics*, 40: 241-275.

GOLDSCHMIDT, DEBORAH AND JOHANNES F. SCHMIEDER (2017), "The Rise of Domestic Outsourcing and the Evolution of the German Wage Structure," *The Quarterly Journal of Economics*, 132 (3):1165â1217.

GONSALVES, COLIN (2011), "Kaliug: The Decline of Human Rights Law in the Period of Globalisation," Human Rights Law Network, New Delhi, India.

HASAN, RANA, DEVASHISH MITRA, AND K.V. RAMASWAMY (2007), Technology Trade Reforms, Labor Regulations, and Labor-Demand Elasticities: Empirical Evidence from India," *Review of Economics and Statistics*, 89(3): 466-481.

HSIEH, CHANG-TAI, AND PETER KLENOW (2014), "The Life-Cycle of Manufacturing Plants in India and Mexico," *Quarterly Journal of Economics*, 129(3): 89-108.

HSIEH, CHANG-TAI, AND BENJAMIN OLKEN (2014), "The Missing Missing Middle," *Journal of Economic Perspectives*, 28(3): 1403-1448.

KAPOOR, RADHICKA, AND P.P. KRISHNAPRIYA (2017), "Informality in the formal sector: Evidence from Indian manufacturing," IGC Working Paper.

KATZ, LAWRENCE F., AND ALAN B. KRUEGER (2019), "The Rise and Nature of Alternative Work Arrangements in the United States, 1995â2015," *ILR Review*, 72(2):382-416.

KLETTE, TOR, AND SAMUEL KORTUM (2004), "Innovating firms and Aggregate Innovation," *Journal of Political* Economy, 112(5): 986-1018.

MATSUURA, KENJI AND CORT J. WILLMOTT (2012), "Terrestrial Percipitation: 1900-2010 Gridded Monthly Time Series," *Univeristy of Deleware*.

SAHA, BIBHAS, KUNAL SEN, AND DIBYENDU MAITI (2013), "Trade Openness, Labour Institutions and Flexibilisation: Theory and Evidence from India," *Labour Economics,* 24: 180-195.

SINGH, JAIVIR, DEB KUSUM DAS, HOMAGNI CHOUDHURY, PRATEEK KUKREJA (2016), "Law, Skills and the Creation of Jobs as "Contract" Work in India: Exploring Survey Data to make Inferences for Labour Law Reform," ICRIER Working Paper 330.

STEEL AUTHORITY OF INDIA LTD. V. NATIONAL UNION WATER FRONT WORKERS, (2001).

A Appendix Tables

Table A.1: District Correlates with Staffing Measure

	Pos. Staffing	log Staffing
Log District Employment	0.565***	0.188***
	(0.110)	(0.069)
Log Avg Firm Size	-0.020	0.056
	(0.058)	(0.036)
Manuf Emp Share	0.034	0.042***
	(0.022)	(0.011)
Manuf Formal Emp Share	0.023	0.050***
	(0.027)	(0.013)
Share Young Firms	-0.010	0.002
	(0.020)	(0.015)
Size Diff Log VA/Worker	0.315	-0.187
	(0.195)	(0.127)
Size Diff Log FT Wage	-0.010	-0.049
	(0.060)	(0.038)

Note: Table reports coefficients from regressions of the outcome variable in each row (in 1990) on staffing measure (also measured in 1990) in each column, with fixed effects for the state. 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 log average product per worker (APL) 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. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table A.2: Staffing Heterogeneity: Robustness to Alternative Decay Rates

	(1)	(2)	(3)
logL	0.040***	0.048***	0.034***
	(0.013)	(0.017)	(0.011)
log VA/Worker	-0.013	-0.008	-0.016
	(0.013)	(0.016)	(0.011)
log VA/Wage-Bill	-0.022**	-0.021	-0.023**
	(0.011)	(0.014)	(0.009)
Decay Parameter	0.0075	0.005	0.01
Wght Emp X Year FE	X	X	X
Firm Controls X Year FE	X	X	X
Dist Controls X Year FE	X	X	X

This table replicates the last column of Table 2 for alternative values of the decay rate κ.* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.3: APL-Firm Size Relationship and 1990s Reform

	log VA/Worker	log VA/Worker
Log L	0.074***	0.086***
	(0.014)	(0.008)
Reform	-0.107**	-0.391***
	(0.050)	(0.050)
Log L X Reform	0.048***	0.112***
	(0.015)	(0.014)
R^2	0.32	0.32
N	401,391	401,391
Reform Measure	Delicense	FDI
Industry FE	X	X
State-Year FE	X	X

Note: Observations at the firm-year level. Data covers 1985-1997. Log L is log non-managerial employment. In column (1) reform measure is a dummy equal to one if all or part of the 3-digit industry is delicensed in that year. In column (2) 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.4: Staffing Industry Over Time

Year	Establishments	Employment	Employment Index
1990	219	1339	1
1998	1138	7679	5.51
2005	12030	53669	16.52
2013	18669	83808	19.82

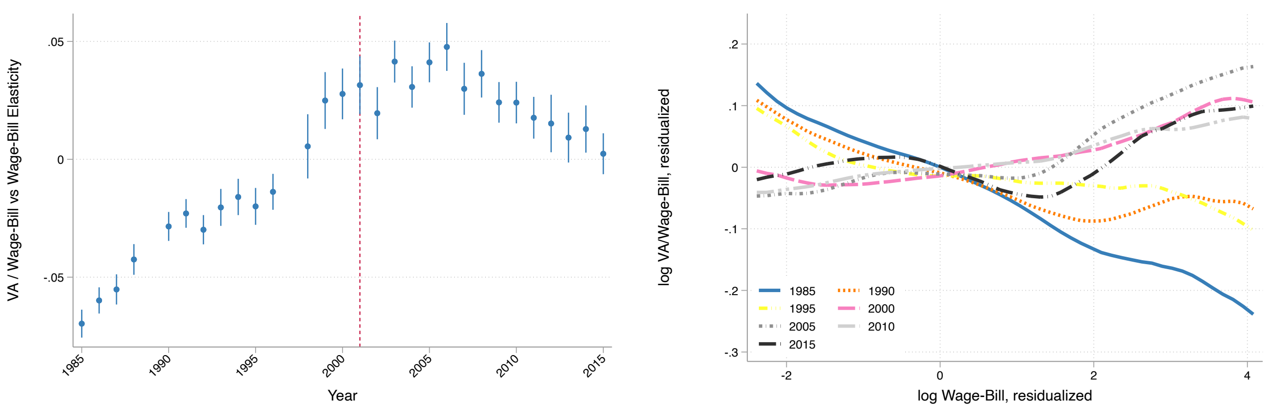
Note: Source is from the Economic Census. Columns total employment and establishments under the 4 digit NIC code associated with staffing firms. Employment reported is workers employed directly in the operations of the staffing establishment, rather than contract workers provided to third parties. Last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

B Appendix Figures

Figure B.1: VA/Wage-Bill vs Wage-Bill Elasticity Over Time

(a) Elasticities by Year

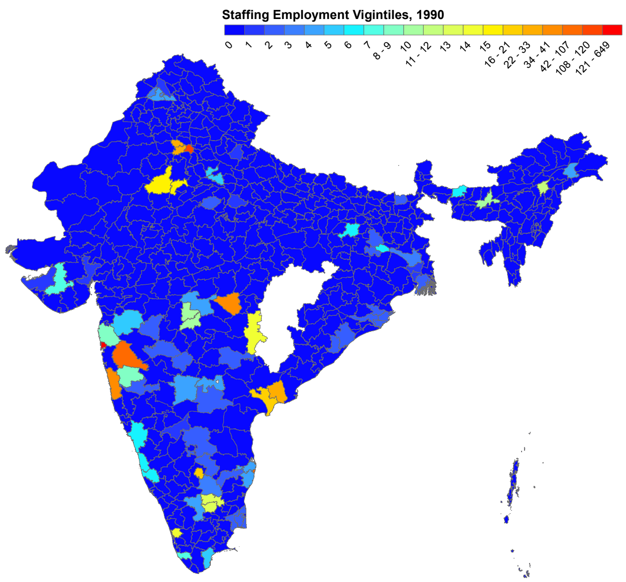
(b) Cross-Section by Year



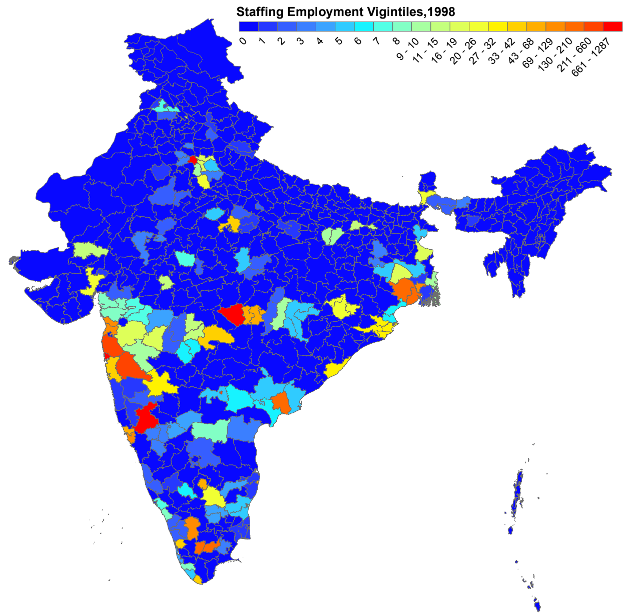
Note: Panel (a) shows elasticity of log VA/Wage-Bill to log Wage-Bill in each year. VA/Wage-Bill is measured as value added over the total cost (wages, bonuses and benefits) of non-managerial workers, while Wage-Bill is the total cost of those workers. Regression is the same as that reported for the VA/Worker and VA/Capital plots in the main text. Panel (b) shows the cross-sectional relationship non-parametrically in each year, where log VA/Wage-Bill is first demeaned by industry and year fixed effects. Confidence bands are omitted for clarity.

Figure B.2: Staffing Industry Growth Over Time

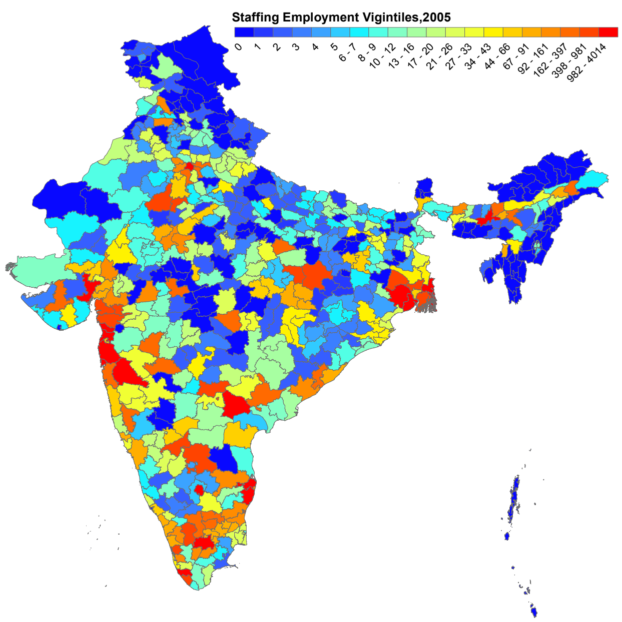
(a) 1990



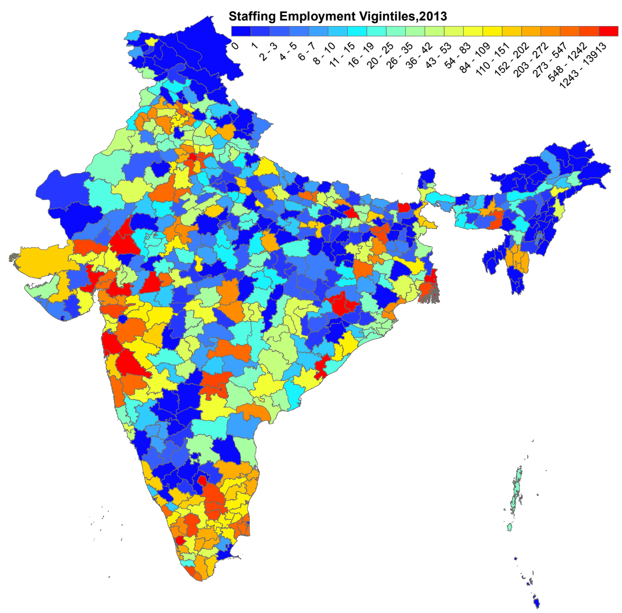
(b) 1998



(c) 2005



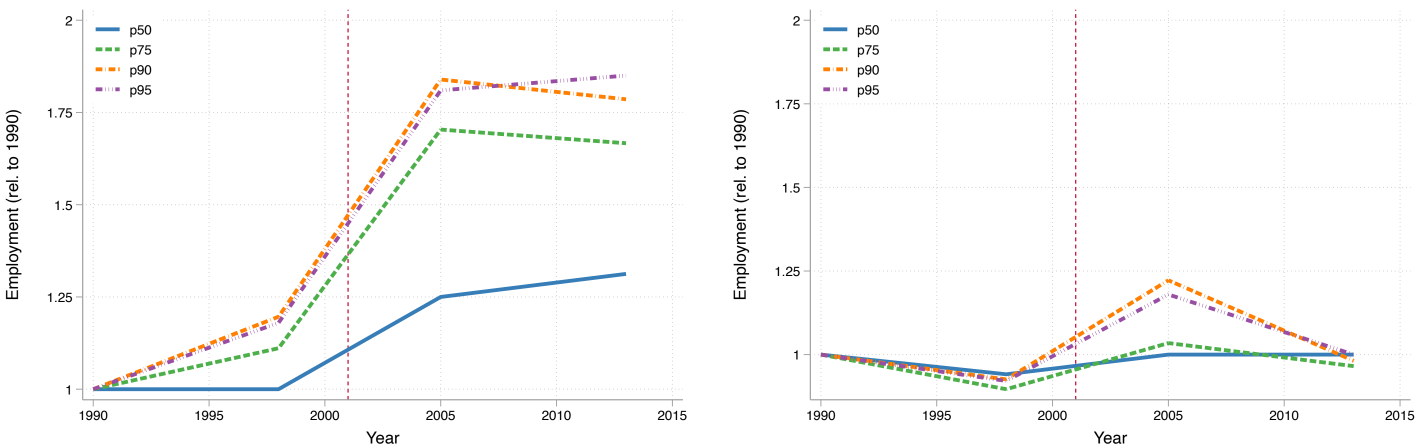
(d) 2013



Note: Data is from the Economic Census. Jammu and Kashmir and parts of Madhya Pradesh missing in 1990 census.

Figure B.3: Manufacturing vs Services Plant Size Distributions Over Time in the Economic Census

(a) Manufacturing (b) Services



Note: Plot shows percentiles of plant employment in manufacturing and service sector establishments from the Economic Census. Data comes from 1990, 1998, 2005 and 2013.

C Theory Appendix

C.1 Value Function Derivation

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

$$V_k(\mathcal{Q}_t) = \max_{x_k} \left\{ \sum_j \left[\begin{array}{c} \Delta \left[\frac{1}{\sigma} \left(1 + [1 - \mathbb{I}_j]\, x\kappa_k\right)^{1-\sigma} \hat{q}_j^{\sigma-1} Y_t - \mathbb{I}_j F Y_t - \xi_k^{-\frac{1}{1-\beta}} x^{\frac{1}{1-\beta}} Y_t \right] + \\ (1 - r\Delta) \left[\begin{array}{c} x\Delta \left[V_{k,t+\Delta}\left(\mathcal{Q}_t \backslash \{q_j\}\right)\right] + \\ x_k \Delta \mathbb{E}\left[V_{k,t+\Delta}\left(\mathcal{Q}_t \cup \lambda q\right)\right] + \\ (1 - x\Delta - x_k\Delta) V_{k,t+\Delta}\left(\mathcal{Q}_t\right) \end{array} \right] \end{array} \right] \right\}$$

where $\mathbb{I}_j = \mathbb{I}\{k(j) = H, \hat{q}_j > \hat{q}^*\}$ is an indicator variable for a product staffed by contract workers. Subtract $(1 - r\Delta)V_k(\mathcal{Q})$ from both sides, rearranging, dividing by Δ and letting $\Delta \to 0$ yields the HJB equation

$$rV_k(\mathcal{Q}) - \dot{V}_k(\mathcal{Q}) = \max_{x_k} \left\{ \sum_j \left[\begin{array}{c} \frac{1}{\sigma} \left(1 + [1 - \mathbb{I}_j]\, x\kappa_k\right)^{1-\sigma} \hat{q}_j^{\sigma-1} Y_t - \mathbb{I}_j F Y_t - \xi_k^{-\frac{1}{1-\beta}} x^{\frac{1}{1-\beta}} Y_t + \\ x\left[V_k\left(\mathcal{Q} \backslash \{q_j\}\right) - V_k(\mathcal{Q})\right] + \\ x_k \left[\mathbb{E}\left[V_k\left(\mathcal{Q} \cup \lambda q\right)\right] - V_k(\mathcal{Q})\right] \end{array} \right] \right\}$$

This provides the first formulation of the value function in the text. Later, we recognize that the state variable can be written as the set of relative productivities $\hat{\mathcal{Q}}_f = \{\hat{q}_j : j \in \mathcal{J}_f\}$. Since all growing variables grow at the same rate, we write the value function in terms of its stationary version $V_k(\hat{\mathcal{Q}}) =$

$\tilde{V}_k(\hat{\mathcal{Q}})Y$. Substituting this, the results below and the expression for flow profits from the text in we get that

$$r\tilde{V}_k(\hat{\mathcal{Q}})Y - \frac{\partial \tilde{V}_k(\hat{\mathcal{Q}})Y}{\partial t} = \max_{x_k} \left\{ \sum_j \left[\begin{array}{c} \frac{1}{\sigma}\left(1 + [1-\mathbb{I}_j]\, x\kappa_k\right)^{1-\sigma} \hat{q}_j^{\sigma-1} Y - \mathbb{I}_j F Y - \xi_k^{-\frac{1}{1-\beta}} x^{\frac{1}{1-\beta}} Y + \\ x\left[\tilde{V}_k\left(\hat{\mathcal{Q}}\backslash\{\hat{q}_j\}\right) Y - \tilde{V}_k(\hat{\mathcal{Q}})Y\right] + \\ x_k\left[\mathbb{E}\left[\tilde{V}_k\left(\hat{\mathcal{Q}} \cup \lambda q\right) Y\right] - \tilde{V}_k(\hat{\mathcal{Q}})Y\right] \end{array} \right] \right\}.$$

Since $\frac{\partial \tilde{V}_k(\hat{\mathcal{Q}})Y}{\partial t} = \dot{\tilde{V}}_k(\hat{\mathcal{Q}})Y + \tilde{V}_k(\hat{\mathcal{Q}})\dot{Y}$, we can divide by Y and rearrange to get

$$(r-g)\tilde{V}_k(\hat{\mathcal{Q}}) - \dot{\tilde{V}}_k(\hat{\mathcal{Q}}) = \max_{x_k} \left\{ \sum_j \left[\begin{array}{c} \frac{1}{\sigma}\left(1 + [1-\mathbb{I}_j]\, x\kappa_k\right)^{1-\sigma} \hat{q}_j^{\sigma-1} - \mathbb{I}_j F - \xi_k^{-\frac{1}{1-\beta}} x^{\frac{1}{1-\beta}} + \\ x\left[\tilde{V}_k\left(\hat{\mathcal{Q}}\backslash\{\hat{q}_j\}\right) - \tilde{V}_k(\hat{\mathcal{Q}})\right] + \\ x_k\left[\mathbb{E}\left[\tilde{V}_k\left(\hat{\mathcal{Q}} \cup \lambda q\right)\right] - \tilde{V}_k(\hat{\mathcal{Q}})\right] \end{array} \right] \right\}$$

since $g = \dot{Y}/Y$.

C.2 Value Function Simplification

Suppose the the value function has form $\tilde{V}_k(\hat{Q}) = \sum_j v_k(\hat{q}_j)$. Then, we have

$$\begin{aligned} (r-g)v_k(\hat{q}_j) - \dot{v}_k(\hat{q}_j) &= \max_x \left\{ \tfrac{1}{\sigma}\left(1 + [1-\mathbb{I}_j]\, x\kappa_k\right)^{1-\sigma} \hat{q}_j^{\sigma-1} - \mathbb{I}_j F - \xi_k^{-\frac{1}{1-\beta}} x_k^{\frac{1}{1-\beta}} - x v_k(\hat{q}_j) + x_k E_{\hat{q},\lambda}\left[v_k(\lambda\hat{q})\right] \right\} \\ \Rightarrow (r-g+x)v_k(\hat{q}_j) - \dot{v}_k(\hat{q}_j) &= \left[\frac{1}{\sigma}\left(1 + [1-\mathbb{I}_j]\, x\kappa_k\right)^{1-\sigma} \hat{q}_j^{\sigma-1} - \mathbb{I}_j F\right] + \max_{x_k \geq 0}\left\{ x_k \mathbb{E}\left[v_k(\lambda\hat{q})\right] - \xi_k^{-\frac{1}{1-\beta}} x_k^{\frac{1}{1-\beta}} \right\}. \end{aligned}$$

Write

$$h(\hat{q}_j) = \left[\frac{1}{\sigma}\left(1 + [1-\mathbb{I}_j]\, x\kappa_k\right)^{1-\sigma} \hat{q}_j^{\sigma-1} - \mathbb{I}_j F\right] + \max_{x_k \geq 0}\left\{ x_k \mathbb{E}\left[v_k(\lambda\hat{q})\right] - \xi_k^{-\frac{1}{1-\beta}} x_k^{\frac{1}{1-\beta}} \right\}.$$

Now the HBJ equation is a linear differential equation:

$$-(r-g+x)v_k\left(\hat{q}_j(t)\right) + \dot{v}_k\left(\hat{q}_j(t)\right) = -h\left(\hat{q}_j(t)\right) \tag{C.5}$$

where $\hat{q}_j(t) = \hat{q}_j e^{-gt}$.

For the low-type firms, the solution is given by

$$\begin{aligned} v_L\left(\hat{q}_j\right) = &\frac{1}{\sigma}\frac{1}{r-g+x+(\sigma-1)g}\hat{q}_j^{\sigma-1} \\ &+ \frac{1}{r-g+x}\max_{x_L \geq 0}\left\{ x_L \mathbb{E}\left[v_L(\lambda\hat{q})\right] - \xi_L^{-\frac{1}{1-\beta}} x_L^{\frac{1}{1-\beta}} \right\}. \end{aligned} \tag{C.6}$$

For high-type firms, the solution is

$$\begin{aligned} v_H\left(\hat{q}_j \middle| \hat{q}_j \leq \hat{q}^*\right) = & \frac{1}{\sigma} \frac{\left(1+x\kappa\right)^{1-\sigma}}{r-g+x+(\sigma-1)g} \hat{q}_j^{\sigma-1} \\ & + \frac{1}{r-g+x} \max_{x_H \geq 0} \left\{ x_H \mathbb{E}\left[v_H(\lambda\hat{q})\right] - \xi_H^{-\frac{1}{1-\beta}} x_H^{\frac{1}{1-\beta}} \right\} \end{aligned} \tag{C.7}$$

if the quality $\hat{q}_j$ is below the threshold $\hat{q}^*$ (i.e., the product line j only employs full-time workers), and

$$\begin{aligned} v_H\left(\hat{q}_j \middle| \hat{q}_j > \hat{q}^*\right) = & \frac{1}{\sigma} \frac{1}{r-g+x+(\sigma-1)g} \hat{q}_j^{\sigma-1} - \frac{F}{r-g+x} \\ & + \left[\frac{1}{\sigma} \frac{\left(1+x\kappa\right)^{1-\sigma} - 1}{r-g+x+(\sigma-1)g} \hat{q}^{*\sigma-1} + \frac{F}{r-g+x} \right] e^{-(r-g+x)\tilde{t}(\hat{q}_j)} \\ & + \frac{1}{r-g+x} \max_{x_H \geq 0} \left\{ x_H \mathbb{E}\left[v_H(\lambda\hat{q})\right] - \xi_H^{-\frac{1}{1-\beta}} x_H^{\frac{1}{1-\beta}} \right\}, \end{aligned} \tag{C.8}$$

if the quality exceeds the threshold $\hat{q}^*$ (i.e., the product line j employs contract workers), where $\tilde{t}(\hat{q}_j) = g^{-1}\left[\ln(\hat{q}_j) - \ln(\hat{q}^*)\right]$ denotes the number of years before the quality will fall below the threshold $\hat{q}^*$. The expressions are intuitive. The first line (in all three expressions) represents the present dicount value of the profit stream (excluding the innovation costs), assuming that the current contract labor adoption decision holds indefinitely. However, in the case that $\hat{q}_j > \hat{q}^*$, the quality will fall below the threshold $\hat{q}^*$ after $\tilde{t}(\hat{q}_j)$ years and the product line will stop employing contract labor. The second line in the last expression adjusts for this future change to contract labor adoption. Finally, the last line in all three expressions represents the present value of the expected future gains from innovation activities. Rearranging and substituting the Euler equation $g = r - \rho$ yields the expressions in the text.

Lastly, solving for optimal innovation intensity gives

$$x_k = \tilde{\beta} \xi_k^{\frac{1}{\beta}} \mathbb{E}\left[v_k\left(\lambda\hat{q}\right)\right]^{\frac{1-\beta}{\beta}}$$

for each type $k \in \{L, H\}$.

C.3 Growth Rate Derivation

Between t and $t+\Delta$, the productivity distribution evolves according to

$$\begin{aligned} F_{t+\Delta}(\hat{q}) &= F_t(\hat{q}(1+g\Delta)) + x\Delta \int_1^\infty F_t\left(\hat{q}/\lambda\right) dG(\lambda) - x\Delta F_t(\hat{q}) \\ \Rightarrow \frac{F(\hat{q}(1+g\Delta)) - F(\hat{q})}{\Delta} &= x\left(F(\hat{q}) - \int_1^\infty F\left(\hat{q}/\lambda\right) dG(\lambda)\right) \end{aligned}$$

where G is the distribution of stepsizes and we consider a BGP so that the distrubution of relative productivities is constant. Since

$$\lim_{\Delta \to 0} \frac{F(\hat{q}(1+g\Delta)) - F(\hat{q})}{\Delta} = f(\hat{q})\hat{q}g$$

we get that

$$g\hat{q}f(\hat{q}) = x\left(F(\hat{q}) - \int F\left(\hat{q}/\lambda\right) dG(\lambda)\right).$$

Integrating over $\hat{q}$ we get

$$\begin{aligned}
E\left[\hat{q}\right] &= x/g \int_0^\infty \left(F(\hat{q}) - \int F\left(\hat{q}/\lambda\right) dG(\lambda)\right) d\hat{q} \\
&= -x/g \left(\int_0^\infty \left[1 - F(\hat{q})\right] d\hat{q} + \int_0^\infty \left[1 - \int_1^\infty F\left(\hat{q}/\lambda\right) dG(\lambda)\right] d\hat{q}\right) \\
&= \frac{x/g}{1 + x/g} \int_0^\infty \left[1 - \int F\left(\hat{q}/\lambda\right) dG(\lambda)\right] d\hat{q}
\end{aligned}$$

since $E\left[\hat{q}\right] = \int_0^\infty \left[1 - F(\hat{q})\right] d\hat{q}$. Inverting the order of integrals, the integral on the right becomes $\int_1^\infty \int_0^\infty \left[1 - F\left(\hat{q}/\lambda\right)\right] d\hat{q} dG(\lambda)$. Using the change of variables $x = \hat{q}/\lambda$ so that $d\hat{q} = \lambda dx$ we get

$$\int_0^\infty \left[1 - F\left(\hat{q}/\lambda\right)\right] d\hat{q} = \lambda \int_0^\infty \left[1 - F\left(x\right)\right] dx = \lambda E\left[\hat{q}\right]$$

The whole integral is therefore $E\left[\hat{q}\right] \int_1^\infty \lambda dG(\lambda)$, so that

$$\begin{aligned}
E\left[\hat{q}\right] &= \frac{x/g}{1 + x/g} E\left[\hat{q}\right] E\left[\lambda\right] \\
&\Rightarrow g = (E\left[\lambda\right] - 1)x
\end{aligned}$$

Using that $E\left[\lambda\right] = \frac{\theta}{\theta - 1}$ under the Pareto distribution gives the result.

Finally, to define the share of products owned by high-type firms ϕ, we use similar manipulations to define the productivity distributions of products owned by low- and high-type firms as

$$\begin{aligned}
F_{H,t+\Delta}(\hat{q}) &= F_H(\hat{q}(1+g\Delta)) + x_H \Delta \int_1^\infty F_t(\hat{q}/\lambda) dG(\lambda) - x\Delta F_H(\hat{q}) \\
F_{L,t+\Delta}(\hat{q}) &= F_L(\hat{q}(1+g\Delta)) + x_L \Delta \int_1^\infty F_t(\hat{q}/\lambda) dG(\lambda) - x\Delta F_L(\hat{q})
\end{aligned}$$

Rearranging and taking the same limit as above, we get the following system of 3 equations defining the productivity distributions $F(\hat{q}), F_L(\hat{q}), F_H(\hat{q})$

$$g\hat{q}f(\hat{q}) = xF(\hat{q}) - x\int_1^\infty F\left(\hat{q}/\lambda\right) dG(\lambda) \tag{C.9}$$

$$g\hat{q}f_H(\hat{q}) = xF_H(\hat{q}) - x_H \int_1^\infty F(\hat{q}/\lambda)dG(\lambda) \tag{C.10}$$

$$g\hat{q}f_L(\hat{q}) = xF_L(\hat{q}) - x_L \int_1^\infty F(\hat{q}/\lambda)dG(\lambda) \tag{C.11}$$

The share of products owned by high type firms is then

$$\phi = F_H(\infty). \tag{C.12}$$

C.4 Static Allocations

The solution to the hiring problem is

$$\ell_j = q_j^{\sigma-1}\left(1 + \left[1 - \mathbb{I}_j\right] x\kappa_k\right)^{-\sigma}\left(\frac{\sigma}{\sigma-1}w\right)^{-\sigma} Y$$

Plugging this back into inverse demand $p_j = \left(\frac{y_j}{Y}\right)^{-\frac{1}{\sigma}}$ yields the price $p_j = \frac{\sigma}{\sigma-1}\left(1 + \left[1 - \mathbb{I}_j\right] x\kappa_k\right) w$. Sales are then $p_j y_j = \frac{\sigma}{\sigma-1}\left(1 + \left[1 - \mathbb{I}_j\right] x\kappa_k\right) w\ell_j$.

Labor market clearing then implies

$$\int p_j y_j dj = \frac{\sigma}{\sigma-1}\left[w \int \left(1 + \left[1 - \mathbb{I}_j\right] x\kappa_k\right)\ell_j dj\right]$$
$$\Rightarrow Y = \frac{\sigma}{\sigma-1} wL.$$

where we normalize the price index to one.[42] Replacing this into the expression for labor delivers $\ell_j = \hat{q}_j^{\sigma-1}\left(1 + \left[1 - \mathbb{I}_j\right] x\kappa_k\right)^{-\sigma} L$, where we define $Q = Y/L$ and $\hat{q}_j = q_j/Q$. Prices and sales are therefore $p_j = \left(1 + \left[1 - \mathbb{I}_j\right] x\kappa_k\right) Q$ and $p_j y_j = \hat{q}_j^{\sigma-1}\left(1 + \left[1 - \mathbb{I}_j\right] x\kappa_k\right)^{1-\sigma} Y$, while profits are given by

$$\pi_j = p_j y_j - \left(1 + \left[1 - \mathbb{I}_j\right] x\kappa_k\right) w\ell_j - \mathbb{I}_j F_k Y$$
$$= \frac{1}{\sigma}\hat{q}_j^{\sigma-1}\left(1 + \left[1 - \mathbb{I}_j\right] x\kappa_k\right)^{1-\sigma} Y - \mathbb{I}_j F_k Y$$

where $F_k = F$ if $k = H$ and $F = 0$ if $k = L$. The definition of the price index then implies:

$$1 = \left(\int \left(\frac{p_j}{q_j}\right)^{1-\sigma} dj\right)^{\frac{1}{1-\sigma}}$$
$$\Rightarrow Q = \left(\int_0^1 \left(\frac{q_j}{1 + \left[1 - \mathbb{I}_j\right] x\kappa_k}\right)^{\sigma-1} dj\right)^{\frac{1}{\sigma-1}}.$$

[42] We assume that the adjustment cost κ is paid in terms of labor.

A high-type firm adopts contract labor for product line j if it is profitable to do so:

$$\frac{1}{\sigma}\hat{q}_j^{\sigma-1}Y - F_jY > \frac{1}{\sigma}\hat{q}_j^{\sigma-1}\left(1+x\kappa\right)^{1-\sigma}Y.$$

This yields the adoption condition $q_j > q^*$ as defined in the text.

Finally, aggregate consumption equals aggregate output minus resources expended on research activities and on fixed costs of hiring contract labor:

$$C = Y - \left[\phi\xi_H^{-\frac{1}{1-\beta}}x_H^{\frac{1}{1-\beta}} + (1-\phi)\xi_L^{-\frac{1}{1-\beta}}x_L^{\frac{1}{1-\beta}} + \xi_E^{-\frac{1}{1-\beta}}x_E^{\frac{1}{1-\beta}}\right]Y - F\int_0^1 \mathbb{I}_j dj\, Y.$$

The share of consumption in output therefore is given by

$$\frac{C}{Y} = 1 - \left[\phi\xi_H^{-\frac{1}{1-\beta}}x_H^{\frac{1}{1-\beta}} + (1-\phi)\xi_L^{-\frac{1}{1-\beta}}x_L^{\frac{1}{1-\beta}} + \xi_E^{-\frac{1}{1-\beta}}x_E^{\frac{1}{1-\beta}}\right] - F\int_0^1 \mathbb{I}_j dj.$$

Since $C_t = Q_0(C/Y)e^{gt}$ along the balanced growth path, welfare $U = \int_0^\infty e^{-\rho t}\ln C_t dt$ is given by

$$U = \frac{1}{\rho}\left[\ln Q_0 + \frac{g}{\rho} + \ln\left(C/Y\right)\right] \quad .$$

D Estimation and Quantification: Simulation Algorithm

D.1 Step 1: Calibration with Pre-Period Moments

1. The moment function takes in a vector of parameters $(x_H, x_L, x_E, \alpha, \kappa, F, \theta)$ as its input.
2. Set the number of products to 2^{14} and specify an initial guess for the distribution of quality across products.
3. Initially, there are 2^{14} entering firms, each of which holds one product.
4. Simulate life paths for the firms. Specifically, each period, both incumbent and entering firms innovate upon products, as specified in Section 6.2. Products change hands accordingly, and some firms exit endogenously as they lose all products. The dynamics is governed by the innovation parameters x_H, x_L, x_E, α, and θ.
5. In addition, in each period, compute employment at each firm. Hiring decision by firms is governed by κ and F.
6. Let the model run until it attains stationarity. We judge that the model has reached a stationary state when fluctuation in the dispersion of log qualities over last 100 periods is less than a certain threshold.[43]
7. Once the model attains stationarity, we compute the targeted moments (specified in Table 6) over 200 periods, and take the average.
8. After 200 periods, we compute the objective. The objective is defined the (weighted) sum of squared percentage deviation of simulated moments from data moments.
9. Repeat 1-8 searching for the set of parameters that minimizes the objective.
10. Recover the deep innovation parameters ξ_H, ξ_L, and ξ_E by inverting equations 1 and 2.

D.2 Step 2: Estimation of Post-Period F

1. The moment function takes in a vector of parameters $(\xi_H, \xi_L, \xi_E, \alpha, \kappa, F, \theta)$ as its input. Note that the moment function now takes in deep innovation parameters ξ_H, ξ_L, and ξ_E estimated in the previous step, rather than the innovation arrival rates x_H, x_L, and x_E.
2. Set the number of products to 2^{14} and specify an initial guess for the distribution of quality across products.

[43] More specifically, the condition is that the variance in the standard deviation of log qualities over last 100 years is less than 0.002.

3. Initially, there are 2^{14} entering firms, each of which holds one product.

4. Simulate life paths for the firms. Specifically, each period, both incumbent and entering firms innovate upon products, as specified in 6.2. Products change hands accordingly, and some firms exit endogenously as they lose all products. The innovation arrival rates x_H, x_L, and x_E are now set endogenously based on the *deep* innovation parameters ξ_H, ξ_L, and ξ_E, as specified in equations 1 and 2.

5. In addition, in each period, compute employment at each firm. Hiring decision by firms is governed by κ and F.

6. Let the model run until it attains stationarity. We judge that the model has reached a stationary state when fluctuation in the dispersion of log qualities over last 100 periods is less than a certain threshold.[44]

7. Once the model attains stationarity, compute the targeted moment (percentage of large firms with intensive contract labor use) over 200 periods, and take the average.

8. Repeat 1-7 searching for F to exactly match the the targeted moment (percentage of large firms with intensive contract labor use in the post-period) in the data, keeping all other parameters (i.e., ξ_H, ξ_L, ξ_E, α, κ, and θ) at the estimated values from the previous step. This yields an estimate for the post-period F.

[44] As above, the condition is that the variance in the standard deviation of log qualities over last 100 years is less than 0.002.

E Estimation and Quantification: Sensitivity Analysis

In this section, we calibrate the model with different values of σ and ψ to assess the robustness of the results to alternative parameterization. We explore three alternative specifications in total. Table E.5 presents selected results from these alternative specifications, which we shall discuss in detail below. (The column "Baseline" reproduces the results from the baseline specification presented in the text.)

E.1 Alternative Specification 1: $\sigma = 1.5$ and $\psi = 0.02$

First, we try lowering σ from 2.0 to 1.5, without changing ψ. The third to last column of Table E.5 presents selected results from the specification. We observe three things. First, the fit of the model is superior to the baseline model; in fact, all the moments are closely matched. Second, as for the parameters, the proportion of high-type firms among entrants, α, is markedly higher than in the baseline specification. A higher α implies that there are more high-type firms in the economy and therefore among top 25% firms. Hence, F in the Pre-period does not need to be as high to match the fraction of large firms with intensive contract labor use in the data. Last, as with the baseline specification, the reduction in F has almost no effect on aggregate innovation rate; the welfare gain, on the other hand, is estimated to be smaller. This is because the estimated reduction in F is smaller. Since there are more high-type firms among top 25% firms than in the baseline specification, F does not fall as much to match the change in the contract labor usage in the data.

E.2 Alternative Specification 2: $\sigma = 2.5$ and $\psi = 0.02$

Next, we try increasing σ from 2.0 to 2.5, without changing ψ. The second to last column of Table E.5 presents selected results from the second specification. We note three things. First. the fit of the model is inferior to that of the baseline model, though all model-generated moments are around the data moments except for the 75th percentile of age. Second, the estimated α is much lower than in the baseline model, which implies there are fewer high-type firms; therefore that the reduction in F has to be markedly larger to fit the trend in the contract labor usage. There being fewer high-type firms also explains why we fail to match the 75th percentile of age; note that high-type firms on average live longer than low-type firms given $x_H > x_L \approx 0$. Lastly, in this specification, the reduction in F results in a small decline in aggregate innovation rate of about 0.3%. The estimated welfare gain is now larger, precisely because the estimated reduction in F is far larger.

E.3 Alternative Specification 3: $\sigma = 2.0$ and $\psi = 0.01$

Last, we keep σ at 2.0 as in the baseline specification, but lower ψ to 0.01. The last column of Table E.5 presents the results from this last specification. We observe three facts. First. the fit of the model is inferior to that of the baseline model. Second, as with Specification 2, the estimated α is lower than in the baseline model, which implies there are fewer high-type firms and therefore that the reduction in F has to be larger to fit the trend in contract labor usage. The large estimated reduction in F implies a larger welfare gain. Last, the impact on aggregate innovation rate is almost zero as it was the case with other specifications.

Table E.5: Alternative Specifications with Different Values of σ and ψ: Selected Results

	Period	Data	Base	Spec 1	Spec 2	Spec 3
Settings						
σ	-	-	2.00	1.50	2.50	2.00
ψ	-	-	0.02	0.02	0.02	0.01
Moments						
Rate of Job Creation by Incumbents	Pre	0.0434	0.0526	0.0387	0.0567	0.0596
Share of Employments in Entrants	Pre	0.0456	0.0365	0.0418	0.0312	0.0307
Difference in Exit Rates by Age Group	Pre	0.0132	0.0134	0.0135	0.0136	0.0131
Average Revenue Product of Labor Elasticity	Pre	0.0444	0.0408	0.0430	0.0391	0.0426
% Large Firms with Intensive Contract Labor Use	Pre	0.2175	0.2168	0.2183	0.2084	0.2084
% Large Firms with Intensive Contract Labor Use	Post	0.3575	0.3597	0.3574	0.3572	0.3584
75th Percentile of Firm Age	Pre	21.00	15.95	20.69	9.23	14.38
TFP Growth	Pre	1.0740	1.0695	1.0741	1.0652	1.0639
Parameter Estimates						
x_H	Pre	-	0.1203	0.0947	0.1774	0.1334
x_L	Pre	-	0.0000	0.0015	0.0022	0.0005
x_E	Pre	-	0.0191	0.0316	0.0129	0.0148
α	Pre	-	0.0255	0.0614	0.0082	0.0199
κ	Pre	-	6.9007	5.5280	4.8623	8.2976
F	Pre	-	1.2119	0.2587	2.2272	3.0389
θ	Pre	-	2.9953	2.4007	4.2643	3.1244
ξ_H	Pre	-	0.2516	0.1775	0.3921	0.2712
ξ_L	Pre	-	0.0027	0.0242	0.0372	0.0156
ξ_E	Pre	-	0.0954	0.1115	0.0895	0.0814
F	Post	-	0.6489	0.1979	1.1645	1.3514
Counterfactuals						
Change in x	-	-	-0.03%	-0.03%	-0.29%	-0.07%
Static Gain in Output	-	-	7.60%	2.63%	10.72%	13.87%

Note: The table presents selected results from alternative specifications where we calibrate the model with different sets of σ and ψ. The first column indicates the period in which the moment or the parameter applies. The second column presents data moments where appropriate. The third column is the results from the baseline model we presented in the text. The last three columns present results from the alternative specifications. The values of σ and ψ used for calibration are noted in the first and second rows. For the detailed notes on figures presented in the third row and below, see notes under Tables 6, 7, 10, and 11. As in the main text, all specifications set $\rho = 0.05$ and β=0.5.