Contract Labor and Establishment Growth in India

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Abstract

India's Industrial Disputes Act (IDA) requires large manufacturing plants to pay substantial costs if they wish to shrink their workforce. Since the early 2000s, these plants have increasingly relied on contract workers who are not subject to these regulatory constraints. Between 2000 and 2015, the contract labor share in non-managerial employment nearly doubled at establishments with more than 100 workers (from 21 to 40 percent percentage points), while it only increased from 14 to 17 percentage points at establishments with less than 50 workers. Over the same period, the thickness of the right tail of the establishment size distribution in formal Indian manufacturing plants increased, the average product of labor for large plants declined, the job creation rate for large plants increased, and the probability that large plants introduced new products rose. We argue that these outcomes were caused by the increased reliance on contract labor among large plants. A model of establishment 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 plants with negligible change in the long-run growth rate.

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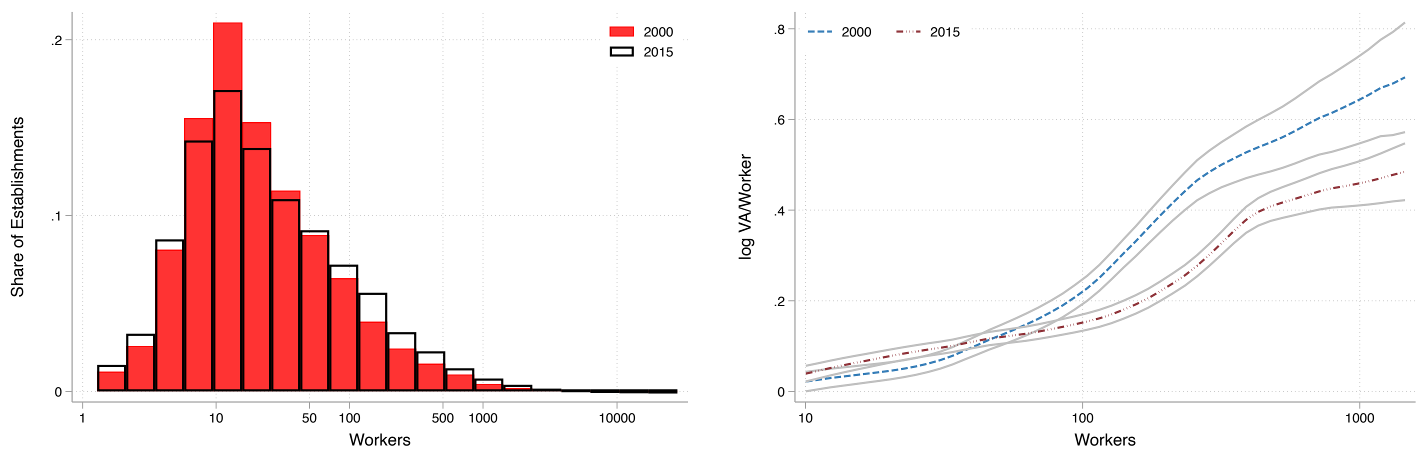
1 Introduction

Many observers have pointed to the Industrial Disputes Act (IDA) of 1947 as an important constraint on growth in India. In particular, Chapter VB of the IDA requires manufacturing plants with more than 100 non-managerial workers that wish to 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 plants are likely to be sub-optimally small. Consistent with this, the Indian manufacturing sector is characterized by a large number of informal plants, a small number of large plants, and a high marginal product of labor in large plants. Second, the higher costs faced by large plants in retrenching workers may dissuade them from undertaking risky investments, which may be one of the forces behind the low life-cycle growth of Indian manufacturing plants.[2]

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

(a) Establishment Size Distribution | (b) VA/Worker vs. Establishment Size



Note: Left panel shows the distribution of plants by 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. Log VA/Worker is residualized by industry-year fixed effects.

This paper argues that the constraints on large plants have diminished since the early 2000s, despite no change to 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 establishment employment in

[1] A 1976 amendment to the IDA made layoff, retrenchment, and closure illegal for all plants with more than 300 non-managerial workers. The threshold was lowered to 100 in 1982, with some states further lowering it to 50. From here on, we use the terms workers and employment interchangeably to refer to non-managerial workers.

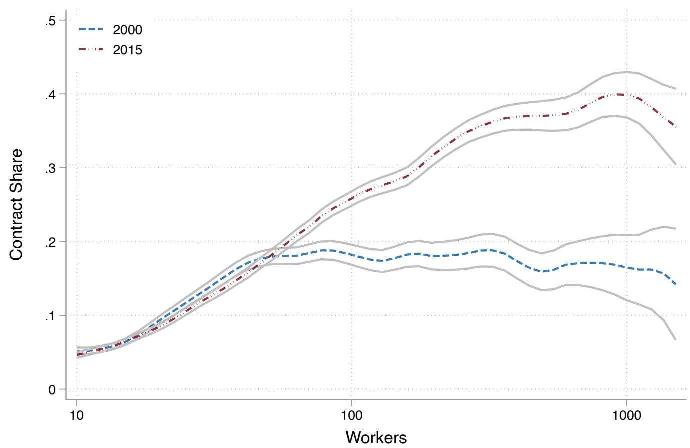
[2] See Hsieh and Olken (2014) on the plant-size distribution in India and Hsieh and Klenow (2014) for evidence on low life-cycle growth in Indian manufacturing.

[3] 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 (Standing Orders) Act of 1946. It has yet to come into force.

2000 and 2015, but this relationship is more attenuated in 2015 compared to 2000, particularly for larger plants. If the marginal product of labor is proportional to the average product, and employers equate the marginal product of labor to the cost, the effective cost of labor has diminished for large Indian plants compared to smaller ones since the early 2000s.[4]

We argue that the main force behind the decline in labor constraints faced by large Indian plants since the early 2000s is these plants' increased reliance on contract workers, hired via staffing companies. The IDA rules regarding severance pay, mandatory notice, and governmental authorization for retrenchment only apply to an establishment's permanent workforce. Hence, plants have the flexibility to return contract workers to staffing companies without being in violation of the IDA.

Figure 2: Contract Labor Use and Establishment Size: 2000 vs. 2015



Note: Plot shows point estimates and 95% confidence intervals from non-parametric regression of the share of workers hired through contractors on (log) employment.

While a legal framework for the deployment of contract labor has been in place since the early 1970s to limit its use to tasks that are non-perennial and not regularly performed by permanent workers, the staffing model started booming in the early 2000s. Figure 2 shows the fraction of establishment workers hired through contractors as a function of total establishment non-managerial employment. While there has been no sizeable change in the share of contract workers at smaller plants, there has been a dramatic increase among larger plants, especially those with more than 100 workers. By 2015, contract workers account for 40% of non-managerial employment at plants with more than 100 workers, compared to 21% in 2000. In contrast, in 2015, contract workers account for only 17% of non-managerial employment at plants with less than 50 workers, just a 3 percentage points increase relative to 2000.

We argue that a decision by the Indian Supreme Court in 2001 played an important role in ex-

[4]Figures 1 and 2 are from India's Annual Survey of Industries described in Section 3.

plaining the explosion of contract labor in India, particularly at larger plants.[5] Prior to this decision, it was unclear whether plants that were "caught" improperly using contract workers in "core" activities would have to absorb these workers into their permanent workforce. This plausibly made large plants reticent to rely too much on outsourcing. The 2001 Supreme Court decision clarified that such absorption was not required. We show that there was a marked change in the use of contract workers by large plants, in the employment share of large plants, and in the gap in labor productivity between large and small plants after 2001. In addition, these changes were more pronounced for plants with closer access to staffing centers prior to the Supreme Court decision.

There are two main channels via which a greater reliance on contract workers may have led to the expansion of large plants and the decline in the value-added per worker at these plants. 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 plants that rely more on contract workers should be more responsive to productivity shocks. Consistent with this channel, the time series evidence reveals both an increased likelihood of large (more than 10%) employment change, as well as an increase in the standard deviation of employment growth at large plants, starting in the early 2000s. Also, using Bartik-style labor demand shocks as well as rainfall shocks at the district level, we show that plants in districts where contract workers are more readily available are more responsive to such demand shocks.

Second, the availability of contract labor may have reduced the extent to which large plants face a higher marginal cost of labor because of greater unionization and other labor cost pressures disproportionately imposed on these plants by the regulatory environment. Consistent with this channel, we find that, while there is a positive and quite stable elasticity of the average cost of labor to establishment 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 plants, and hence the average cost of labor goes down for larger plants 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 plants: the elasticity of permanent labor cost to establishment size is positive but started trending down in the early 2000s, especially in districts closer to staffing centers. We further argue that compositional differences between permanent and contract workers cannot account for these changes.

We corroborate all of these findings in an establishment-year panel that controls for establishment fixed effects as well as industry-year specific shocks. We show that an establishment'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

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

report evidence suggesting that reliance on contract labor makes plants more dynamic and more likely to change their product mix.

We use a model of creative destruction with heterogeneous establishments to quantify the effect of contract labor in the presence of the IDA. The model features two types of establishments. Innovative, high-type establishments expand over time by producing new products, while stagnant low-type plants do not innovate and remain small. We model the IDA as an adjustment cost faced by high-type plants whenever they fire workers. The anticipation of future retrenchment causes large plants 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 plants by assuming that plants subject to the IDA can circumvent firing costs by hiring contract workers after paying a fixed cost.

We estimate the reduction in this fixed cost that matches the rise in the share of contract labor within large plants 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 plants on the gap in value-added per worker between large and small plants, 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 plants seen in Figure 1. This decline represents less static misallocation of labor and accounts for 7.6% of the overall increase in manufacturing TFP over this period. However, our results suggest the aggregate growth rate did not change due to the proliferation of contract labor. On the one hand, the plants subject to the IDA innovate more as its bite is reduced when they use more contract labor. On the other hand, entrants (who are more likely to be of the 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 literature on the rise of non-standard work arrangements.[6] In the case of the rise of contract work in India, most relevant to our work is Chaurey (2015) who shows that establishments located in states with more stringent labor regulations hire relatively more contract workers in response to weather-induced transitory local demand shocks. The evidence in Chaurey (2015) is consistent with the hypothesis that establishments facing the most stringent labor regulation might be hiring contract workers to get around the strict

[6] Katz and Krueger (2019), Goldschmidt and Schmieder (2017), Drenik et al. (2020), and Felix and Wong (2021) document the rise of temporary work arrangements in the U.S., Germany, Argentina and Brazil, respectively.

labor laws. In an industry-state-year panel, Saha et al.(2013) find a positive relationship between import penetration and the share of contract workers; they also find that pro-worker legislation and greater bargaining power of permanent workers (as proxied for by the lockout-to-strike ratio or union density) increases the share of contract workers. Kapoor and Krishnapriya (2017) study the rise in the use of contract labor in the Indian manufacturing sector between 2000 and 2012 across states and industries and document greater use of contract workers in establishments where the gap in average wage between permanent and contract workers is smaller, which they view as consistent with establishments using contract workers to suppress the bargaining power of regular workers. We are not aware of any research directly using the SAIL judgment as a source of temporal variation in the size of the contract workforce to explore its implications for misallocation and productivity growth in the formal Indian manufacturing sector.

Second, we develop a model of creative destruction with heterogeneous plants and size-dependent firing costs to quantify their effect on aggregate TFP. A strand of existing theoretical work seeks to quantify the effects of such policies.[7] However, in these models, establishment productivity is exogenous and thus cannot account for how such policies might affect productivity growth. In this paper, we extend Klette and Kortum's (2004) model of endogenous innovation to incorporate size-dependent firing costs.[8] This allows us to quantify the effect of these frictions on TFP, through impacts on both 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, and much work since has sought to isolate particular causes of misallocation. This paper provides evidence for Indian manufacturing that it is large rather than small plants that face higher frictions in the labor markets, and shows that this gap is driven in part by size-dependent firing costs using a quasi-experimental policy change that reduced these frictions.[9]

Lastly, our paper contributes to the literature on the economic impact of labor regulation in India.[10] We provide new evidence on how large plants subject to the IDA were able to circumvent this

[7]See for example Hopenhayn and Rogerson (1993) and Guner, Ventura, and Xu (2008).

[8]Other papers that extend Klette and Kortum (2004) include Acemoglu et al. (2018), Akcigit and Kerr (2018), Akcigit et al. (2021), and Aghion et al. (2021). Our model is closest to that in this last paper, which analyzes the effect of size-dependent restrictions in France.

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

[10]Fallon and Lucas (1993) show that the 1976 amendment of the IDA, which mandated plants employing 300 or more workers to request permission from the government prior to retrenchment, lowered formal employment by 17.5%. Dutta Roy (2004) also finds that plants 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 plants 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 reform and industrial licensing reform, respectively.

law by employing contract workers and trace the impacts of this de-facto reduction in labor regulation on the Indian formal manufacturing sector.

The paper is organized as follows. Section 2 lays out the institutional background. Section 3 describes data sources. Section 4 provides a simple theory to illustrate the possible forces behind the observed increased use of contract labor, highlighting differences between markers in the data of supply vs. demand shocks. Section 5 provides various empirical tests in support of a causal relationship between the rise in the supply of contract labor and the increase in establishment size and decline in average product labor at larger plants. In Section 6, we investigate two mechanisms via which contract labor may have freed up establishment growth: reduction in labor adjustment costs and reduction in the cost of labor. Section 7 develops and estimates our structural model. Section 8 discusses the implications of the rise of the staffing model for workers and sketches a model to quantify its distributional effect across groups of more and less educated workers. We conclude in Section 9.

2 Contract Labor in India

A central piece of labor legislation in India is the Industrial Disputes Act (IDA, 1947), which lays out the conditions for hiring and retrenching workers, as well as for the closure of plants. In particular, a 1976 amendment to the IDA (Chapter VB) stipulates that all plants with more than 300 workers need to get government authorization for any layoff, retrenchment, or closure. This coverage was extended in 1982 to all plants with more than 100 workers, with some states further reducing this threshold to 50 workers.[11] Unapproved separations carry a potential punishment of both a substantial fine and a prison sentence for the employer.[12] [13]

However, a loophole exists in the IDA that can theoretically enable large plants to skirt some of its requirements. The application of severance pay, mandatory notice, or governmental retrench-

[11]The IDA defines a worker, which it refers to as a "workman" as: "any person (including an apprentice) employed in any industry to do any manual, unskilled, skilled, technical, operational, clerical or supervisory work for hire, whether the terms of employment be expressed or implied..." The definition further explicitly excludes individuals working in managerial and administrative tasks. It does not differentiate between part-time and permanent work. Establishment size for purpose of IDA coverage is based on the number of "workmen ... employed on an average per working day for the preceding twelve months."

[12]Actual compensation for retrenchment if granted is 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]Other aspects of the IDA and related laws impose additional costs on plants with a large number of workers. For example, the Industrial Employment (Standing Orders) Act requires establishments 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), meaning that no employer can effectuate any change in the conditions of service of any worker without giving 21 days of notice. The IDA also sets conciliation, arbitration and adjudication procedures to be followed in the case of an industrial dispute and empowers national or state governments to constitute Labour Courts, Tribunals, National Tribunals, Courts of Inquiry, and Boards of Conciliation. See Ahsan and Pages (2007).

ment authorization only applies to permanent workers. Hence, by resorting to contract labor, a large employer could theoretically bypass some of the most restrictive regulations of the IDA.

Indian legislators began to address this loophole in 1970 when they passed the Contract Labour (Regulation and Abolition) Act (CLA, 1970). This Act was enacted "to regulate the employment of contract labour in certain plants and to provide for its abolition in certain circumstances."[14] The CLA requires that all plants with 20 or more contract workers obtain a registration for employing such labor and that all staffing agencies with 20 or more employees be government-licensed.[15] Contract workers covered under the CLA have rights related to working hours, safety and health, social security (under the Employees' State Insurance Act of 1948) and retirement benefits (under the Employees' Provident Funds and Miscellaneous Provisions Act of 1952).

Most importantly, Section 10 of the CLA limits employers' ability to deploy contract workers as a way to get around the IDA's requirements. Under Section 10, contract workers are *de jure* not supposed to be in charge of tasks within an establishment that are perennial in nature and typically completed by permanent workers in that industry. The Act gives government the authority to prohibit or "abolish" contract labor at any establishment that uses this labor for its "core" operations.

The CLA, however, left vague what would happen to the contract workers at an establishment subsequent to the government issuing a notification under Section 10 banning the establishment from using this labor. In particular, there was uncertainty as to whether, subsequent to an abolition notification, the employer would be required to automatically absorb the contract 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.

The liberalization of the Indian economy in 1991 gave Indian employers a stronger impetus to get around the IDA and find ways to bring in more contract workers in their workforce (Gopalakrishnan and Mirer, 2013). In response to industry pressures, some state governments eased up the licensing procedures for labor contractors and started making amendments to the legislation on contract labor (Saha and Sen, 2014). Employers also started lobbying for a reform of Indian labor laws, including Chapter VB of the IDA, as well as for the scrapping of Section 10 of the CLA (Gopalakrishnan and Mirer, 2013). These legislative lobbying efforts went nowhere, likely because of strong opposition from the trade unions.

At the same time, employers also started arguing before the Courts that the CLA did not require the absorption of contract workers into the permanent workforce. Following a series of earlier ju-

[14] https://clc.gov.in/clc/acts-rules/contract-labour-regulation-abolition-act-1970.

[15] According to a report by *Staffing Industry Analysts*, the three largest staffing companies in India by 2012 were Adecco, Teamlease and Randstad and these three companies accounted for about 15 percent of the total market; the market share of the top ten staffing companies was about 26 percent. See https://www2.staffingindustry.com/row/Editorial/Daily-News/India-Adecco-is-largest-staffing-firm-in-a-USD-5-Billion-market-28900.

dicial decisions (some pro-employers; some pro-workers), a 2001 ruling by the Supreme Court of India, which overturned a prior 1997 ruling, lifted the uncertainty about absorption requirements in employers' favor. In its *Steel Authority of India Limited v. National Union Water Front Workers* judgment (the "SAIL" judgment), the Supreme Court ruled that there is no requirement for automatic absorption of contract workers in the permanent workforce subsequent to an abolition notification.

The SAIL judgment has been deemed by various observers as critical in the rise of contract labor in India. Gonsalves (2011) writes: "A legal right, to permanent employment of the contract workers where the contract labour system has been abolished, goes a long way to reducing the prevalence of the contract labour system throughout India. The stand that no such right exists on abolition will achieve quite the opposite." Similarly, Landau et al. (2015) note: "The implications of this shift have proven significant and contentious, with unions abandoning their strategic use of s. 10(1) of the Act as a means of securing permanency for contract workers." Several authors (e.g., Sankaran, 2012; Cox, 2012; Sundar, 2012) describe the SAIL decision as "de facto" deregulation without any changes to the labor laws.

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. In a survey of about 100 Haryana-based manufacturing plants conducted in 2015, Singh et al. (2016) found that the large majority of surveyed plants that use contract workers report having contract and permanent workers work side by side. 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 plants."

In support of this claim, Table 1 shows the top 10 occupations of permanent and contract workers in formal manufacturing in 2018 based on worker-level data from India's Consumer Pyramids Household Survey (CPHS).[16] In particular, both groups of workers share the same three most common occupational categories: industrial and machine workers; plant and machine, industrial machine operators; supervisors, shift-in-charge, workshop managers. These 3 occupations account for nearly 70 percent of contract workers' employment and nearly 60 percent of permanent workers' employment. Seven out of the 10 most common occupations for permanent workers are also represented in the top 10 for contract workers. This is in contrast to developed country settings where contract workers tend to work in occupations peripheral to the plant, such as security, cleaning, logistics, and catering.[17]

Table 2 further shows that there are no marked differences in educational attainment between both types of workers. On the other hand permanent workers are substantially older (by nearly 4

[16] We defer to the next section (and Appendix C) for a fuller description of the CPHS data. 2018 is the earliest year for which we can perform this tabulation.

[17] See Goldschmidt and Schmieder (2017).

Table 1: Top 10 Occupations for Contract and Permanent Workers in Formal Manufacturing

Rank	Contract Workers Occupation	Share	Permanent Workers Occupation	Share
1	Industrial and machine workers	51.45%	Industrial and machine workers	42.16%
2	Plant and machine, industrial machine operators	8.21%	Supervisors, Shift-in-charge, Workshop Managers	9.04%
3	Supervisors, Shift-in-charge, Workshop Managers	7.78%	Plant and machine, industrial machine operators	7.30%
4	Tailors, Dressmakers, Dress designers	3.56%	Metal Moulders, Welders	6.24%
5	Metal Moulders, Welders	2.86%	Office, bank clerks, court clerks, office assistants	4.63%
6	Peons, cleaners and helpers	2.25%	Tailors, Dressmakers, Dress designers	3.74%
7	Liftmen, watchmen, security guards	1.96%	Plant and Machinery Mechanics and Repairers	2.49%
8	Plant and Machinery Mechanics and Repairers	1.62%	Engineers	2.30%
9	Engineering and Industrial Designers	1.52%	Traditional hand embroiders, cloth block printers	1.97%
10	Engineers	1.52%	Machine technicians, Mechanical engineering technicians	1.93%

Note: Sample includes temporary and permanent workers employed in non-managerial occupations in the formal manufacturing sector. Table reports the mean across 3 waves of the CPHS between Jan 2018 and Dec 2018, where each observation within a wave is weighted with the CPHS sampling weight.

years) than contract workers. There is also some evidence that permanent workers belong to more advantaged groups in society (more likely to be males, less likely to belong to the schedule castes), which may reflect discriminatory barriers in accessing the rare permanent positions in the Indian formal economy. The last column restricts the sample to workers with less than 10 years of schooling, and shows that among this less educated group there are no differences in the fraction with more than 5 years of education between permanent and contract workers.

3 Data

Our primary source of data is the Annual Survey of Industries (ASI) conducted by India's Statistical Office (NSSO). The ASI collects data between April of a given year until the end of March the following year. When we refer to the year of the ASI, we refer to a survey that began in April of that year. The ASI is a census of "large" formal Indian manufacturing plants and a random sample of "smaller"

Table 2: Characteristics of Formal Manufacturing Workers: Permanent vs. Contract

	Age	$>$ 10 Years	$>$ 12 Years	Female	Upper Caste	Scheduled Caste	$>$ 5 Years
Permanent Worker	3.770***	0.004	-0.004	-0.034**	0.024	-0.082***	-0.023
	(0.450)	(0.018)	(0.022)	(0.010)	(0.016)	(0.019)	(0.048)
Constant	34.989***	0.805***	0.541***	0.073***	0.180***	0.261***	0.631***
	(0.320)	(0.013)	(0.016)	(0.007)	(0.012)	(0.015)	(0.033)
R^2	0.13	0.07	0.11	0.11	0.15	0.06	0.13

Note: Table shows coefficients from a regression of the worker's characteristic (shown in each column) on a permanent status dummy variable with industry and state fixed effects. Sample in columns 1-6 includes temporary and permanent workers employed in non-managerial occupations in formal manufacturing (Nobs=3,860). Column 7 only includes workers with $<$ 10 years of schooling (Nobs=727). Analysis is based on CPHS' May-Aug 2017 wave using weights for population aged 15 or higher. Robust standard errors reported. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

formal plants.[18] For most years, plants with more than 100 workers are in the census sector, although the size threshold for inclusion in the census sector changes over time.[19] Our main analysis is based on the ASI from 1980 to 2015.

The key variables we use from the ASI are establishment ID (available between 1993 and 2015), district identifiers (available until 2009), value-added, employment, labor compensation, electricity usage, book value of capital, and main industry of the establishment at either the 4 or 5 digit level. The ASI provides information on the number of workers directly employed by the establishment and workers hired through contractors (hereafter referred to as "permanent" and "contract" workers).[20] Wages, bonuses, and benefits for all workers are reported in all years, and a breakdown between permanent and contract workers is provided in a subset of years.[21] The ASI also provides information on the number of "managerial" and "non-managerial" workers, as well as wages, bonuses, and benefits for these two types of workers.

Our secondary dataset is the Center of Monitoring of the Indian Economy (CMIE)'s India-wide representative Consumer Pyramids Household Survey (CPHS). It is a panel survey of nearly 160,000 households across India. CPHS surveys are carried out in a "wave" of 4-months, which each household (and its members) being surveyed 3 times a year.

[18]The 1948 Factories Act requires that plants with more than 20 workers be formally registered (the threshold is 10 workers if the plant uses electricity).

[19]Up until 1996, the census sector consists of plants with more than 100 workers, and plants not in the census sector are sampled by state and 3-digit sector, with roughly one-third probability. Between 1997 and 2003, only plants with 200 or more workers were included in the census sector, and smaller plants were sampled by state and 3-digit sector roughly with one-seventh probability. The census sector reverted to all plants over 100 workers between 2004 and 2014, and plants outside the census sector were sampled by state and 4-digit industry with roughly one-fifth probability. Starting in 2015, the size threshold for inclusion in the census sector varied entirely by state.

[20]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."

[21]Wages for permanent and contract workers are separately provided between 1998 and 2015; the same is true for bonuses and benefits between 1998 and 2007.

The information we use from the CPHS are income, sex, occupation, educational attainment, age, industry (at the 2 digit level), labor market arrangement (self-employed, permanent, contract, daily wage, not-employed), caste, access to a provident fund, and the sampling weight that makes each wave nationally representative. We define a worker as "formal" if they report having access to a provident fund, and informal if they do not. Appendix C shows that the total number of workers and the share of contract workers in the CPHS sample of formal workers in manufacturing is comparable to that in the ASI (which only surveys formal manufacturing plants). Therefore, unless otherwise indicated, we restrict the CPHS to workers in the formal manufacturing sector to make the CPHS sample comparable to the ASI.[22]

4 Contract Labor: Supply vs. Demand

We sketch a model of supply and demand for contract workers to illustrate the forces behind the increased use of contract labor observed in the data. The goal is to show that the increased use of contract labor by large plants can be driven either by an increase in the supply of contract labor or by an increase in the demand for contract labor, but that the declining gap in the average product of labor between large and small plants can only be due to higher supply of contract labor. In Section 7 we use this model, after endogenizing the innovation rates, to estimate the effect of an increased use of contract labor on aggregate TFP.

Aggregate output is $Y = \left(\int_0^1 (q_j y_j)^{\frac{\sigma-1}{\sigma}} dj\right)^{\frac{\sigma}{\sigma-1}}$ where y_j denotes quantity and q_j 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 permanent (employed directly by the establishment) or contract (employed via a staffing company). The two types of workers are perfect substitutes in production and are paid the same wage w. This formulation is isomorphic to one where the two types of workers differ in quality but are perfect substitutes when adjusted for quality. In this case l_j is the number of workers in quality-adjusted units, and the observed wage gap reflects the quality gap between the two types of workers.[23]

An establishment is a collection of varieties so differences in establishment size reflect differences in the number of products they own and the average quality of these products. There are two types of plants, a "high" type and a "low" type, that differ in two ways. First, high-type plants, on average, own a larger number of products compared to low-type plants.[24] Second, to capture the effect of the

[22] See Appendix C for more details on how we use the CPHS to construct the relevant samples of workers. For some of the results, we also use the Economic Censuses, rainfall data from Matsuura and Willmott (2012), and measures of industry-level reforms occurring between 1985 and 1997 from Aghion et al. (2008).

[23] Appendix F.5 considers a model where full time and contract workers are imperfect substitutes even after adjusting for quality. The Appendix also present a model where a plant adds management layers as a function of the demand for its products.

[24] In section 7, we follow Klette and Kortum (2004) and endogenize the distribution of products across plants as the result

IDA, we assume that high-type establishments face firing costs for their permanent workers while low-type establishments do not.

We assume contract workers can be fired at zero cost (by all plants) but the employer needs to pay a fixed cost F for each product line they are employed on. Given the fixed cost of employing contract workers and the assumption that permanent and contract workers are perfect substitutes, a low-type establishment will always employ permanent workers. Revenue per worker of such plants is given by $\left(\frac{\sigma}{\sigma-1}\right) w$ and the same for all varieties owned by low-type plants.

A high-type establishment may choose to employ permanent workers on some product lines and contract workers on other product lines. The critical variable is the probability that the establishment will be forced to retrench when another establishment innovates on its products, which occurs with probability x. If the high-type establishment chooses to employ permanent workers on a product line, it faces an additional labor cost $x\,\kappa\,w\,\ell$. Conditional on employing permanent workers, profit-maximizing labor productivity is given by $\left(\frac{\sigma}{\sigma-1}\right) w\,(1 + x\,\kappa)$ which is higher than the labor productivity of low-type plants due to the firing cost.

A high-type establishment can avoid the retrenchment cost by paying a fixed cost F to employ contract workers. In this case, profit maximizing labor productivity is given by $\left(\frac{\sigma}{\sigma-1}\right) w$. It will choose to do this when the flexibility gains from employing contract relative to permanent workers exceeds the fixed cost F.[25] Average labor productivity of high-type plants is thus a weighted average of labor productivity of products that use permanent workers and products that use contract workers. The gap in average labor productivity between high- and low-type plants thus depends on the share of products for which the high-type establishments employ permanent workers, where this share depends on the fixed cost F of hiring contract workers.

This model captures two key facts about contract labor in India. First, larger plants are more likely to be high-type plants because such plants have a larger number of products, and thus are more likely to employ contract labor. This is consistent with the evidence in Figure 2 that larger plants are more likely to hire contract labor. Second, larger plants pay on average higher labor costs because they are more likely to be high-type plants that face a higher cost for the product lines on which they choose to only employ permanent workers. This captures the fact in Figure 1 that the average product of labor is higher in larger plants compared to smaller plants.

Remember that high-type plants can avoid paying a higher cost for permanent workers by hiring contract workers, and the extent to which they do this depends on the fixed cost. Therefore, a reduction in this fixed cost makes high type firms choose to employ contract labor for more of their

of an innovation process. We also assume that high-type plants innovate more frequently compared to low-type plants so that in steady state high-type plants have on average more products compared to low-type plants.

[25] A high-type establishment will employ contract labor on product lines where the quality exceeds the threshold quality $q^* \equiv \frac{\sigma}{\sigma-1} w \left[1 - (1 + x\kappa)^{1-\sigma}\right]^{\frac{1}{1-\sigma}} (\sigma F)^{\frac{1}{\sigma-1}}$.

products. This increases the share of contract labor in the employment of high type firms. It also decreases the average product of labor for such firms because they now employ costly permanent workers on a smaller number of their products.

Now suppose instead that there is no change in the fixed cost of contract workers but instead there is an increase in the share of establishments that are high type. This will obviously increase the aggregate demand for contract labor. However, more demand for contract labor does not lower the average cost of labor faced by high type plants, and thus can not explain a decrease in the average product of labor of large establishments relative to that of small establishments seen in the data.

5 Did the Rise in Contract Labor Free up Establishment Growth?

In this section, we examine the effect of specific supply shifters on contract labor use and the average product of labor at plants that increased their use of contract workers. First, we conduct an event study analysis around the SAIL judgment in 2001, which we argued plausibly lifted the constraints on the use of contract labor by large Indian plants. Second, we examine the heterogenous effect of the SAIL judgment in districts with greater vs. lesser proximity to staffing centers prior to SAIL. Third, we conduct within-establishment analysis to study changes in establishment outcomes associated with the hiring of contract workers.

5.1 Effect of SAIL Event in the Time Series

The SAIL judgment in 2001, by freeing up the use of contract workers, may have weakened the additional constraints large plants faced compared to smaller plants because of the IDA. 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 use of contract workers across plants in different size categories over time. Panel (a) regresses the share of contract labor in non-managerial employment on year dummies interacted with establishment size indicators: a dummy for whether the plant has 20-49, 50-99, 100-499, and more than 500 workers (relative to the omitted category of plants with less than 20 workers).[26] We then plot the estimated establishment size coefficients for each year, as well as the 95% confidence intervals.

The figure reveals some divergence starting around the SAIL decision between larger and smaller plants. In particular, the relative representation of contract workers at plants with less than 20 work-

[26] Also included in the regression are industry-year fixed effects, and standard errors are clustered at by industry. All figures include establishments with more than 10 workers (the cutoff for inclusion in the ASI given that all plants in the ASI use electricity) and less than the 99th percentile of workers. We also winsorize the 1% tails of continuous, unbounded variables.

ers and plants with between 20 and 49 workers has remained roughly stable throughout the time period under study. In contrast, while there is substantial overlap in the contract labor share between plants with between 20 and 49 workers and those with more than 50 workers over the 1990s, a statistically and economically significant gap emerges post-SAIL. In particular, plants with 100 workers or more, but especially those with 500 workers or more, experience a continuous relative increase in their contract labor share until the early 2010s.

The figure also indicates some rise in the contract labor share at establishments above the 50 workers threshold in the 1990s, which is likely a reflection of some of the easing on contract labor usage in some Indian states following economic liberalization measures in 1991 (See Section 2). The figure also makes it clear that a break in that pre-trend emerges around the SAIL decision, with a remarkable acceleration in the use of contract labor at larger establishments.[27]

Panel (b) estimates the same regression as Panel (a) but instead uses a dummy for whether contract labor represents at least 50% of an establishment's workers as a dependent variable. This is a relevant alternative dependent variable as the Supreme Court's ruling that no absorption of the contract workforce is required may have made plants more willing to take the risk of relying on contract workers for a large share of their operations. The patterns in Panel (b) are consistent with those in Panel (a). While only 14 percent of plants with 20 to 49 workers relied on contract labor for at least half of their workers in 2015, 34 (40) percent of plants with 100-499 (more than 500) workers did.

We next examine whether the timing of the changes in the establishment size distribution also coincides with the SAIL case. Figure 4 plots the 50th, 75th, 90th and 95th establishment size percentiles for manufacturing and services using the Economic Census rounds from 1990, 1998, 2005 and 2013. The left panel shows the sustained growth in the upper percentiles of manufacturing establishments around SAIL. The 90th and 95th percentile establishments has around 55 percent larger employment in 2013 compared to 1998, with slightly less growth at the 75th percentile.[28]

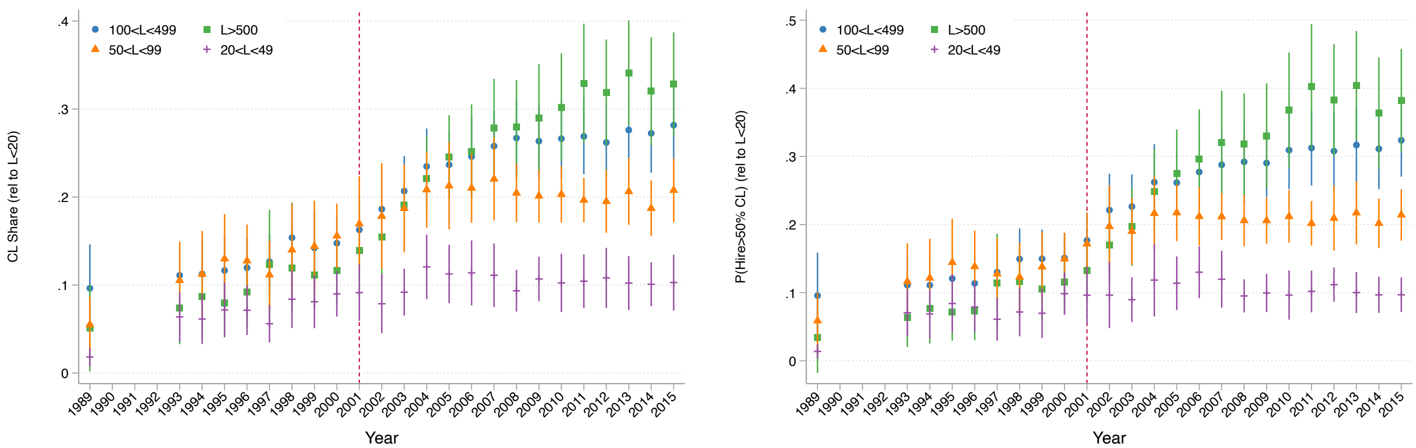
The right panel in Figure 4 shows the growth in the upper percentiles of service sector establishments. While the IDA as a whole applies to all sectors, Section VB, which covers the majority of restrictions on retrenchments, applies only to manufacturing establishments, mines, and plantations with more than 10 workers. Since the firing restrictions of the IDA did not apply to services, there

[27] The contract labor share also increases in plants with between 50 and 99 workers until about 2005, when it stabilizes until the end of the sample period. It is unsurprising that at least some of these plants may have opted to increase their reliance on contract labor, as they might be on the margin of exposure to Chapter VB through future employment growth. It is also possible that the use of contract workers lowers the bargaining power of permanent workers that increases with establishment size (we will later show evidence consistent with this). If so, some establishments with less than 100 workers may also employ contract labor for this purpose when secured that they will not need to absorb this workforce upon "abolishment."

[28] Appendix Figure B.1 repeats this figure using the annual manufacturing data from the ASI, and shows this growth in the right-tail of the size distribution starts right after the SAIL decision in 2001. The Economic Census data considers the universe of formal and informal establishments while the ASI reports only formal employment, and therefore the changes in percentiles differs between the ASI and the Economic Census.

Figure 3: SAIL and Contract Labor Use by Establishment Size

(a) Contract Labor Share (b) Contract>50% Employment

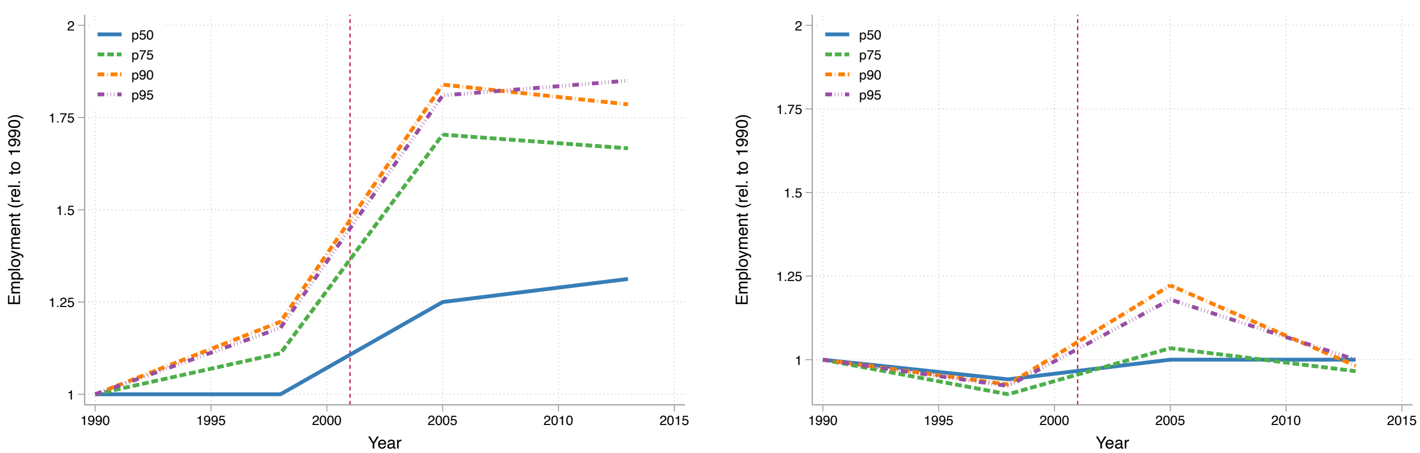


Note: Plot shows coefficients and 95% confidence intervals on regression of outcome on year-industry dummies and year dummies interacted with each size category for employment (with less than 20 workers the omitted category). Standard errors are clustered at industry-level.

was no comparable change in the size distribution of establishments in services over the period when contract labor grew.

Figure 4: Manufacturing vs Services Plant Size Distributions Over Time

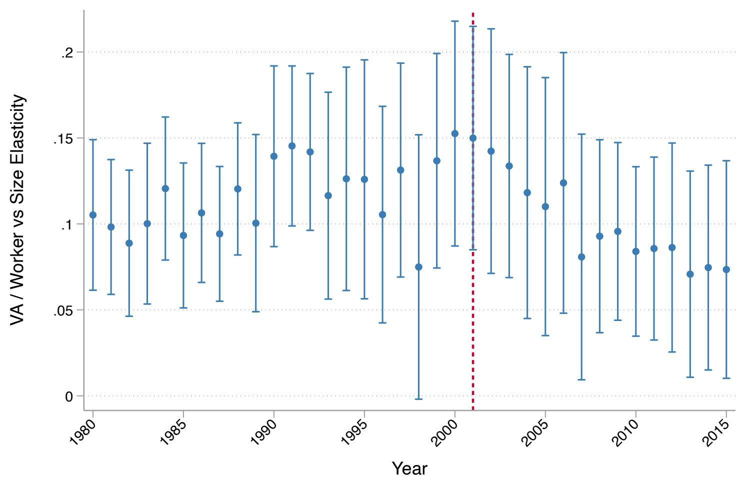
(a) Manufacturing (b) Services



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. See Figure B.1 for finer plot for manufacturing data using annual data from the ASI.

Figure 5 examines the timing of the change in the elasticity of value-added per worker with respect to establishment size. If the marginal product of labor is proportional to the average product and plants equate marginal products with factor costs, this elasticity measures the extent to which large plants face higher effective costs of labor than small plants. We regress log value-added per worker on log employment interacted with year dummies (and a full set of industry by year fixed effects) from 1980 to 2015, and plot the coefficient on log employment in each year.[29] The elasticity shows some increase between the late 1980s and the early 2000s, possibly because the reforms that began in 1991 removed most licensing restrictions and reservations for small plants, which may have made the labor constraints of the IDA more binding.[30] More importantly, Figure 5 shows that the elasticity of the average product of labor to establishment size fell after the early 2000s, possibly due to the SAIL event.[31]

Figure 5: Elasticity of VA/Worker to Establishment Size



Note: Plot shows coefficients and 95% confidence intervals from regressions of log VA/Worker (APL) on log plant employment interacted with year fixed effects. Regressions also include full set of industry-year fixed effects. Standard errors are clustered at the industry-level.

[29]Unlike Figure 3 this plot relies only on total employment, not broken down by permanent or contract, and therefore can be provided contiguously from 1980 to 2015. We trim 1% tails of VA / worker to reduce the influence of outliers, as we do with other continuous and unbounded variables used in the analysis. Appendix E.3 recreates this plot using the wage bill to measure labor inputs.

[30]An earlier version of the paper showed that industries for which restrictions on FDI were lifted experienced large increases in this elasticity during the 1990s, with a smaller and imprecise increase in industries which delicensed.

[31]Appendix E.10 shows that the break in trend in these elasticities around SAIL is significant. The appendix also reports three robustness checks. First, we provide alternate versions of Figure 5 in Figure E.5 that adjust for possible differences in effective labor supplied by permanent and contract workers. Second, while the ASI does not provide firm identifiers so we cannot group plants into firms, it does provide information in certain years on the number of establishments operated by the firm which operates the plant. Appendix E.1 reproduces the results in this subsection on a sample of plants owned by single-plant firms, and shows that the results are virtually identical. Third, the SAIL judgment may have changed the incentives for (large) plants to misreport employment of contract workers, so that the changes we document could be driven by changes in reported rather than actual employment. Appendix E.2 argues against this misreporting concern by analyzing how both electricity use and sales respond when plants hire permanent and contract workers.

5.2 Heterogeneity of SAIL Event

We examine heterogeneity across Indian districts based on the initial supply of staffing companies in the district. The Contract Labor Act requires that plants 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 plants that were geographically closer to such staffing centers.

To isolate the supply of staffing plants uncorrelated with demand-side forces that may have spurred growth of the sector after the SAIL decision, we measure a district's proximity to staffing plants 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 plants providing staffing services, those close by still had access to these plants and the staffing industry as a whole radiated outwards from these initial clusters over time.[32]

We measure district d's proximity to staffing employment in 1990 as $\sum_{k\neq d} e^{-\kappa \text{dist}_{kd}} L^{\text{Staffing}}_{k,1990}$ where dist_{kd} is the number of kilometers between the centroids of districts d and k, $L^{\text{Staffing}}_{k,1990}$ is the number of workers employed by staffing plants in district k in 1990, and κ controls the rate at which the weight on surrounding staffing employment decays with distance.[33]

Table 3 assesses whether the increase in the use of contract labor after SAIL was larger among plants located in districts that were closer to staffing employment. We regress a plant's contract labor share (columns 1 and 2) and the probability a plant hires more than 50% of its workforce through contractors (columns 3 and 4) 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 3 shows that the 2001 SAIL shock is more pronounced in districts that are closer to staffing centers. The point estimates are essentially unchanged when we include interactions between year dummies and a vector of 1990 district level controls (even columns).[34]

Table 4 then analyzes how employment and output per worker of the average plant in the district changed after SAIL in districts with greater access to staffing plants in 1990. We measure the change in

[32]See Appendix Figure B.2 for this evidence. Using the distance-weighted proximity will be valid so long as the location of staffing plants in 1990 was unrelated to future trends in unobservables that affect manufacturing labor demand. Appendix Section E.4 shows the characteristics of districts where staffing plants (i) initially located in 1990 and (ii) grew between 1990 and 2013. The evidence suggests that location choices of staffing plants in the early 1990s were unrelated to labor demand from manufacturing and instead were correlated with demand from the service sector.

[33]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 parameter in Appendix Table A.1. 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.

[34]These 1990 district-level controls, listed in the table notes, are the seven variables that are significantly associated with the staffing measure in Appendix Table E.8.

Table 3: 1990 Staffing and Growth of Contract Labor Use in Manufacturing Plants

	CL Share	CL Share	P(Hire>50%)	P(Hire>50%)
ln Staffing × Post	0.012**	0.011*	0.015***	0.014*
	(0.005)	(0.007)	(0.006)	(0.008)
N Obs	593,338	562,468	593,338	562,468
N Clusters	437	367	437	367
R^2	0.20	0.20	0.17	0.17
State × Year FE	X	X	X	X
Industry × Year FE	X	X	X	X
District Controls × Year FE		X		X

Note: Observation is an establishment-year. Dependent variables are the establishment's share of workers that are contract workers (CL Share) and a dummy for whether the plant hires more than 50 percent of workers through contract labor (P(Hire>50%)). 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 district total employment, average formal manufacturing plant size, the 90th percentile of log formal manufacturing plant size, average log value added per worker, the difference in log value-added per work between large and small plants, log proximity to manufacturing employment in 1990 constructed in the same way as the staffing measure, and log proximity to staffing employment constructed in the same way, all measured in 1990. Standard errors clustered at district level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

these two outcomes for the average plant in a district, which includes the change within individual plants and the effect of plant entry and exit. 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. The table begins by including state-year and industry-year fixed effects, and then sequentially adds in establishment and district controls.

Table 4 shows that average plant employment grew by more (row 1) and value-added per worker declines by more (row 2) after 2001 in districts with greater exposure to staffing, although the the differential decline in the average product of labor is noisy.[35] The results in columns 1-5 are an unweighted average across plants within a district. Since the variation in staffing is at the district level, Column 6 shows the results are robust to using a plant's share of district employment instead.

5.3 Establishment-Year Panel Analysis

Since the ASI includes plant identifiers from 1993 to 2015, we can exploit the panel structure to estimate within-establishment changes associated with the use of contract labor in regressions with establishment fixed effects. We report this analysis in Table 5. Each entry in the table corresponds to a different regression. Reported in the cell is the coefficient on the contract labor use variable. We consider both a dummy variable for any contract labor use and a dummy variable for contract labor accounting for at least 50% of employment. All regressions control for state-year fixed effects and industry-year fixed effects. We restrict the sample to the set of plants that use contract labor at any

[35] Appendix Table E.6 shows the effect becomes sharper when measuring labor inputs via the wage bill.

Table 4: Heterogeneous Outcome Growth Post-SAIL by 1990 Staffing

	(1)	(2)	(3)	(4)	(5)	(6)
log Employment	0.044***	0.061***	0.056***	0.057***	0.046***	0.055*
	(0.017)	(0.021)	(0.016)	(0.016)	(0.017)	(0.032)
N Obs.	589,576	589,576	577,649	547,668	547,668	547,668
N Clusters	437	437	437	367	367	367
log VA/Worker	-0.022*	-0.024	-0.024*	-0.016	-0.020	-0.053
	(0.011)	(0.015)	(0.013)	(0.014)	(0.017)	(0.033)
N Obs.	469,598	469,598	459,745	436,595	436,595	436,595
N Clusters	436	436	436	367	367	367
State × Year FE	X	X	X	X	X	X
Industry × Year FE	X	X	X	X	X	X
Wght Man Emp × Year FE		X	X	X	X	X
Establishment Controls × Year FE			X	X	X	X
Basic Dist Controls v Year FE				X	X	X
Wght Serv Emp × Year FE					X	X
District Emp Share Wghts						X

Note: Observation is an establishment-year. Each entry corresponds to the coefficient from a regression of the outcome in each row on the log staffing measure interacted with a Post-SAIL dummy. Each column corresponds to a specification. Wght Man Emp refers to log proximity to manufacturing employment in 1990 constructed in the same way as the staffing measure. Establishment controls include dummies for plant ownership and organization type as well as a polynomial in establishment age. District controls include log district total employment, average formal manufacturing plant size, the 90th percentile of log formal manufacturing plant size, average log value added per worker, and the difference in log value added per work between large and small plants. Wght Serv Emp refers to an additional control that is log proximity to service employment measure (computed similarly to the log staffing measure). The last column weights by each establishment's share of district employment (all other columns weight by sampling weights). Standard errors clustered at the district-level.* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

point in time, whether or not they use contract labor in a particular year. The results show that size increases (column 1) and value-added per worker falls (column 2) when plants begin to use contract labor.[36]

6 How Did the Rise of Contract Labor Free Up Establishment Growth?

In this section, we look for evidence for two channels through which the use of contract workers may have benefited large plants in India. First, the more widespread availability of contract workers may have prompted large Indian plants 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 permanent workers.

[36] In Appendix Section E.6, we present event study analyses where we plot the evolution of these key outcomes in the years that precede and follow the first hiring of contract labor.

Table 5: Correlates of Contract Labor Hiring Within Plants

	Employment	VA/Worker	Inaction	Job Creation	Add Product
Contract	0.369***	-0.210***	-0.028***	0.115***	0.008*
	(0.013)	(0.010)	(0.005)	(0.006)	(0.004)
Contract $> 50\%$	0.365***	-0.236***	-0.026***	0.136***	0.009*
	(0.016)	(0.017)	(0.007)	(0.006)	(0.005)

Note: Sample are plants that use contract labor at any point in time. Entries report the coefficient from a regression of the outcome on a dummy for the years in which the establishment hires contract workers (any contract worker in row 1 and contract workers for more than 50% of its employment in row 2). Employment and VA/Worker are in logs. Inaction is defined as a dummy for whether a plant's employment growth rate is less than 10% in absolute value. Job creation rate is a plant's employment growth rate $g_{it} = \frac{L_{it}-L_{it-1}}{0.5\times(L_{it}+L_{it-1})}$ for expanding plants and zero otherwise. Add Output Product is a dummy for whether a plant adds a new 5-digit product to its output line up relative to the previous year. All regressions include state-year, industry-year, and establishment fixed effects. Standard errors clustered at the industry-level.* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

6.1 Reductions in Labor Adjustment Costs

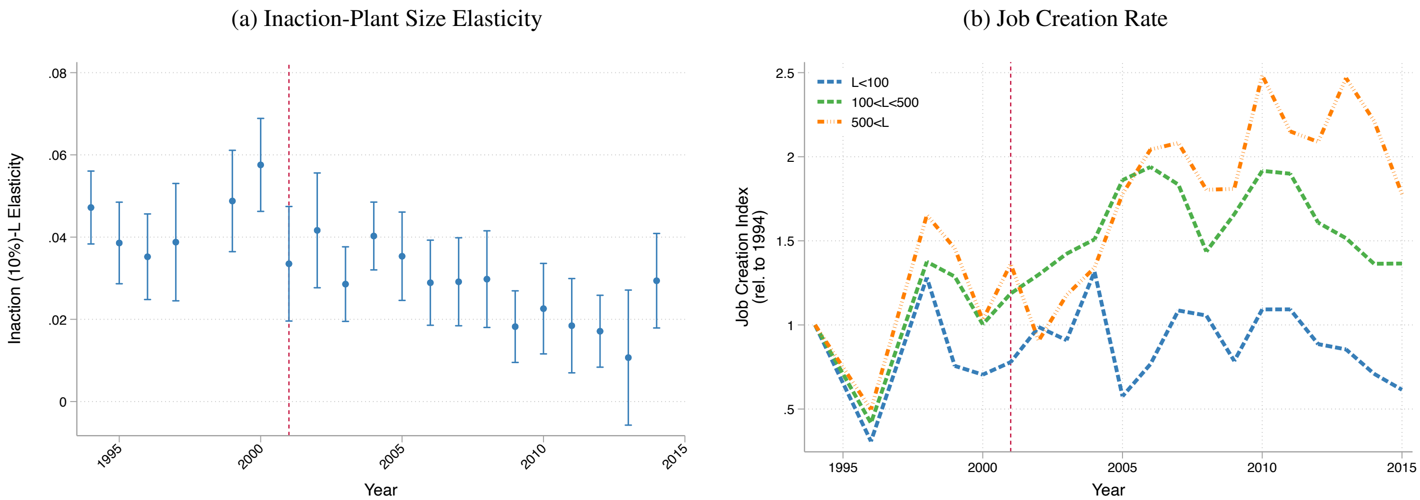
When an establishment receives a positive labor demand shock that may be reversed in the future, the firing cost can make it reluctant to expand - large plants subject to a moderate positive shock today will not hire additional workers with the knowledge that they will most likely have to fire them in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

Consider first the time-series around SAIL in Figure 6. For panel (a), we first define in the establishment-year data a variable called "inaction" to which we assign a value of 1 if the establishment did not change its 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 6 shows the coefficients on log employment for each year. Throughout the sample period, the likelihood of inaction increases with establishment size. Most relevant to us, and consistent with a decrease in relative adjustment costs at large plants post-SAIL, is the decline in the strength of this inaction to establishment size elasticity after 2001.[37] Panel (b) displays the gross job creation rates by establishment size over time (relative to 1994).[38] Here again, we observe an uptick in job creation by larger plants starting in the early 2000s relative to plants with fewer than 100 workers.

[37]Figure B.3 repeats Panel (a) for two alternative ways of measuring plant "inaction" or employment dynamism.

[38]We calculate the job creation rate from expanding plants in each size bin. From this sample, the job creation rate for each size is the ratio of the sum of employment change across expanding plants in each size bin divided by the average of total establishment employment in each size bin at the beginning and end of each period. A period is one year.

Figure 6: SAIL and Employment Dynamics



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 employment interacted with year fixed effects. Regression also includes full set of industry-year and state-year fixed effects, a 4th order polynomial in plant age and dummies for the organization and ownership type of the establishment, all interacted with year fixed effects. Standard errors are clustered at the industry-level. 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).

Another way to examine whether labor started to appear like a more flexible input post-SAIL is to compare it to another flexible input such as electricity. We do this by comparing the dispersion of the average revenue products of labor and electricity (within industry-year cells) over time in Figure 7, where the dispersion of each input is normalized to 1 in 2001.[39] Panel (a) shows that while the dispersion of the average revenue product of electricity is stable before and after SAIL, the dispersion of the average product of labor falls by about 25% beginning right after the SAIL decision. Panel (b) shows this is driven mostly by large plants with more than 100 workers.

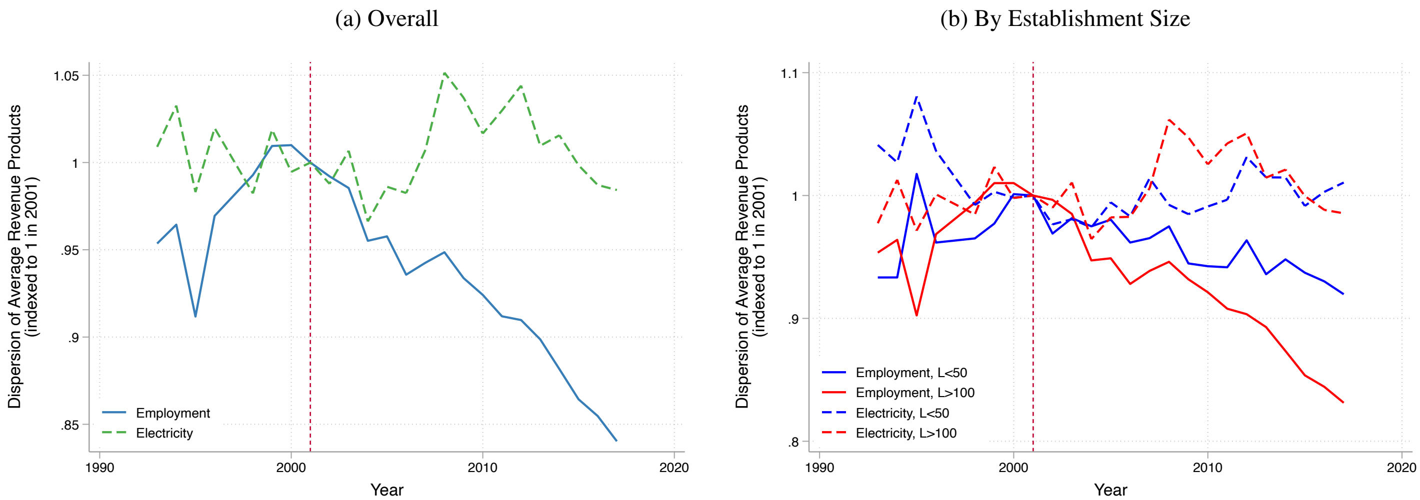
The establishment-year panel analysis in Table 5 also provides evidence of such greater dynamism when a given establishment uses contract labor. The last three columns in Table 5 show that an establishment is less likely to be in the inaction range, the job creation rate is higher, and is more likely to add new products to its output portfolio when it has contract workers on its rolls.[40]

We next examine the effect of contract labor to the sensitivity of plant employment 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

[39]We define dispersion of a variable as its standard deviation. The figure plots the dispersion of the residuals from a regression of the log average product of labor and the log average product of electricity on industry-year fixed effects.

[40]Appendix E.5 examines whether plants produce riskier products when they use contract labor. We find that the added products are neither more nor less risky than the products they made previously.

Figure 7: SAIL and the Dispersion of Average Revenue Products of Labor and Electricity



Note: Both figures begin by regressing the average revenue products of labor (VA/worker) and electricity (VA/KWH) on industry-year fixed effects. Panel (a) then computes the dispersion of the residuals from this regression for each input, normalizing each series to 1 in 2001. Panel (b) does the same but breaking down by plants with less than 50 workers or more than 100 workers. Dispersion defined as the standard deviation.

manufacturing employment and run regressions of the form:

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

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 plants 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.[41] To measure predicted employment growth 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.[42]

Column 1 of Table 6 presents the first stage, which shows that the instrument has good predictive power for district-level employment changes. The slope is 0.789, 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 3. Again, the instrument has good predictive power.

We then examine how the initial contract share of a district (computed between 1997 and 1999) affects the responsiveness of actual employment growth to predicted employment growth during the 2000s. The results suggest that contract labor has a significant effect on responsiveness to shocks:

[41] The ASI only provides district identifiers until 2009. We pool years into a pre- and post-period to increase precision.
[42] We exclude own-district employment when computing national industry growth rates, and standardize the contract share to have zero mean and unit standard deviation.

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). Columns 8 and 9 replicate columns 5 and 6 but use the district's access to staffing employment in 1990 (as computed in Section 5.2) as an alternative measure of access to staffing employment.

Table 6: Contract Labor and Responsiveness of District Employment to Local Bartik Labor Demand Shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Predicted Emp Growth	0.789***	0.761***	0.978***	0.892***					
	(0.130)	(0.147)	(0.126)	(0.174)					
Initial Contract Measure			-0.065	-0.064	-0.063	-0.027	-0.022	-0.140	-0.088
			(0.082)	(0.080)	(0.090)	(0.077)	(0.080)	(0.091)	(0.109)
Predicted Emp Growth × Initial Contract Measure			0.449**	0.421*	0.616**	0.515**	0.491**	0.794***	0.561***
			(0.222)	(0.220)	(0.263)	(0.212)	(0.234)	(0.193)	(0.202)
R^2	0.48	0.47	0.50	0.49	0.54	0.60	0.62	0.57	0.59
N Obs	390	335	390	335	385	335	335	385	335
F-Stat	36.41	27.73							
State FE	X	X	X	X	X	X	X	X	X
District Controls		X		X		X			X
State FE × Pred. Emp Growth					X	X	X	X	X
District Cont. × Pred. Emp Growth							X		
Staffing Measure								X	X

Note: Observations at district level. Outcome is the growth in district ASI employment between 1997-1999 and 2007-2009. Predicted Emp Growth is predicted employment growth rate according to the Bartik measure using the aggregate rate of employment growth across industries in all other districts. Initial contract measure is share of plants 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). Regressions weighted by the district's average number of observations across both pre- and post-periods. Controls are same as in Table 3. Standard errors clustered by district.* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 7 moves the analysis back to the establishment-year panel. Here we follow Chaurey (2015) and use annual rainfall in a district as an alternative economic shock. The variable "shock" in Table 7 takes the value of 1 if rainfall in the establishment'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 establishment's district in that year is above the 80th percentile in the district's distribution, and 0 otherwise.[43] The dependent variable in all regressions is log employment.[44]

[43] Adhvaryu et al. (2013) show that rainfall shocks are associated with drops in agricultural production, wages, and district per capita expenditure.

[44] All regressions include establishment fixed effects, state-year fixed effects, industry-year fixed effects and interact district level conditions in 1990 with year dummies.

The patterns in Table 7 are consistent with the view that the use of contract labor helped reduce labor adjustment costs after the SAIL decision. Column 1 shows that there was no differential responsiveness of employment to shocks overall in the post-SAIL period. However, column 2 shows that plants employing a higher fraction of their workforce through contractors fired more workers in response to negative rainfall shocks than those employing less contract labor after SAIL. Column 3 shows that the employment responses to rainfall shocks become more pronounced amongst large plants relative to small ones. Finally, column 4 shows that greater employment responses to rainfall shocks post SAIL in plants located in districts that are closer to staffing employment in 1990.

Table 7: Contract Labor and Responsiveness of Establishment Employment to Rainfall Shock

	(1)	(2)	(3)	(4)
Shock	0.007	0.002	0.004	-0.032*
	(0.006)	(0.006)	(0.006)	(0.018)
Shock × Post	-0.005	0.007	0.000	0.057**
	(0.008)	(0.009)	(0.008)	(0.024)
Contract		0.609***		
		(0.022)		
Contract × Post		0.266***		
		(0.024)		
Shock × Contract		0.042**		
		(0.017)		
Shock × Contract × Post		-0.089***		
		(0.022)		
Large			1.127***	
			(0.020)	
Large × Post			0.139***	
			(0.013)	
Shock × Large			0.015	
			(0.010)	
Shock × Large × Post			-0.039***	
			(0.011)	
Staffing × Post				0.030**
				(0.014)
Shock × Staffing				0.013**
				(0.005)
Shock × Staffing × Post				-0.019***
				(0.007)

Note: Observations at the establishment-year level. Outcome is log 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 district's distribution, -1 when above the 80th percentile and 0 otherwise. Contract Share is the establishment's share of workers hired through contractors. Large is a dummy for whether the establishment 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. All regressions include establishment fixed effects, state-year fixed effects, industry-year fixed effects and district controls-year fixed effects. District controls are same as in Table 3. Standard errors clustered at the district level.* p <0.1; ** p <0.05; *** p <0.01

6.2 Reductions in the Cost of Labor

A more widespread reliance on contract labor may reduce the cost of labor, especially so for larger plants. The difference in cost between contract and permanent workers might be particularly large for plants that are more regulated, as these plants 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. Furthermore, an increased reliance on contract labor may lower the wage of permanent workers by lowering their bargaining power.

Does Contract Labor Cost Less? Panel (a) in Figure 8 plots the elasticity of average wages with respect to total employment over time. The average wage is defined as the total wage bill for non-managerial workers divided by the number of workers. As before, we first regress log average wage on log employment interacted with year dummies, as well as a full set of industry-year dummies and report 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 quite stable at about .14 from 1980 to 2001, there is a break in trend in the early 2000s when the elasticity starts sharply declining, dropping to about .075 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 plants. 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 rather stable elasticity of daily labor cost to establishment size (except for two outlier years) from 1980 to 2001 of about .18, and a break in trend in the early 2000s, with the elasticity reaching .1 by the end of the sample period.

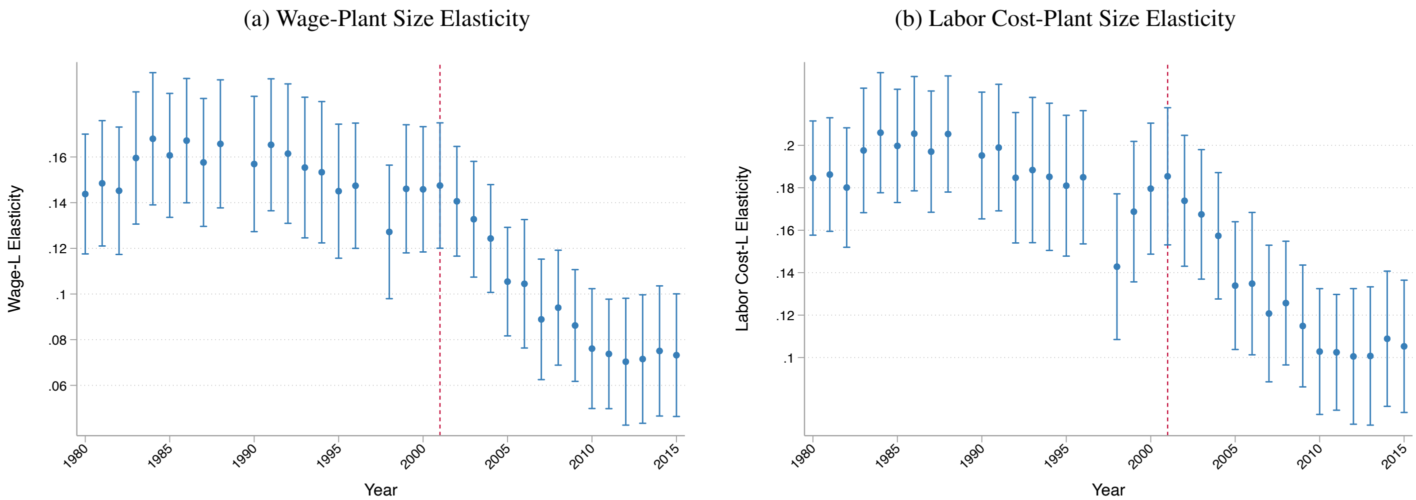
While suggestive of a reduction in the average cost of labor induced by the rise of contract labor, it is possible that they reflect changes in the composition and quality of workers.

To address this possibility, we measure the wage gap between permanent and contract workers holding constant the composition of employment within the establishment in a flexible fashion. For each type of labor $\ell \in \{\text{Contract}, \text{Permanent}\}$ we run the following specification for establishment i in year t:

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

where $W_{\ell it}$ is the average daily wage of type-ℓ workers, γ_{ktb} are industry-year-bin fixed effects, and b is a group indicator for the share of contract workers at establishment i. We bin the contract labor share into five groups depending on whether the establishment 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 plants with

Figure 8: Labor Cost and Plant Size Over Time



Note: Figures plot coefficients and 95% confidence intervals from regression of log wage per worker (panel (a)) and log labor cost per worker (defined as wages, bonuses and benefits in panel (b)) on log employment interacted with year fixed effects. Regressions also include full set of year-industry fixed effects. Standard errors clustered at the industry-level.

different shares of work contracted out. Although our evidence in Table 1 suggests that the tasks performed by contract and permanent workers are quite comparable, these controls allow for the effect of worker composition to vary within each industry-year cell.

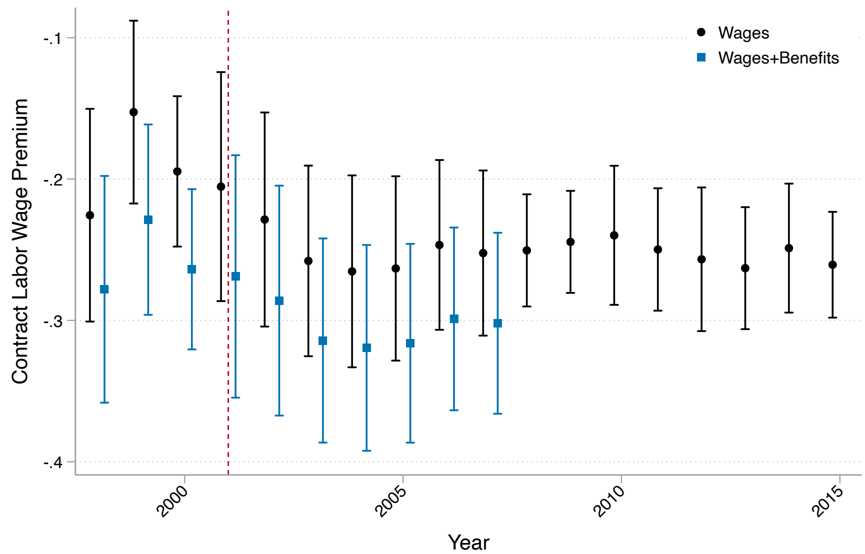
Figure 9 plots the estimates of β_t, which identifies the average wage difference between contract and permanent workers. We also repeat the analysis using total labor costs (wages, bonuses, and benefits) as the outcome variable.[45] Contract workers are about 25% cheaper than permanent workers in terms of wages, and about 30% cheaper in terms of overall payments. After some swings in the late 1990s and early 2000s, these wage and labor cost differences appear quite stable across the 2000s, even though confidence intervals are large.

In Appendix E.8, we use CPHS data to measure the wage gap between permanent and contract workers after controlling for worker characteristics. We estimate that contract workers earn about 25% less than observationally similar permanent workers, which lines up with the wage gap estimated in the ASI.

Does Contract Labor Bring Down Costs Disproportionately for Large Plants? More relevant for our purpose is assessing whether the relative price of contract workers (compared to permanent workers) differs by establishment size. In panel (a) of Figure 10 we plot the raw non-parametric relationship between the relative wage of contract workers and total plant employment in 2000 and 2015. Consistent with the view that the difference in the cost between permanent and contract workers is greater

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

Figure 9: 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 permanent 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. Standard errors clustered at the industry-level.

for large plants, we observe a downward sloping relationship. Consider the relationship in 2000: in plants with 10 workers, contractors are paid about 10% ($\exp(0.1) - 1) \times 100$) less than permanent staff, but this difference increases to 25% (65%) in plants with 100 (1000) 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 plants, and one of the reasons why the rise in contract labor may have reduced the gap in labor cost between larger and smaller plants.

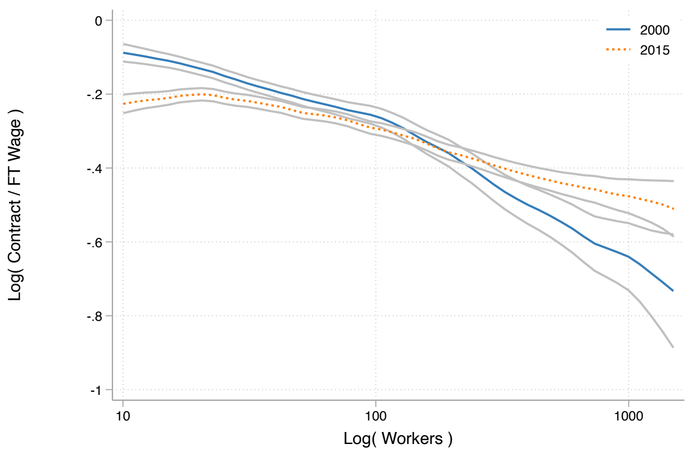
Furthermore, we also observe that this relationship flattens in 2015 compared to 2000 for plants with more than 100 permanent workers, yet is almost identical for smaller plants. In other words, the relative cost of contract workers increased disproportionately over the 2000s for large plants. In panel (c) we explore the timing of this change by estimating the following regression:

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

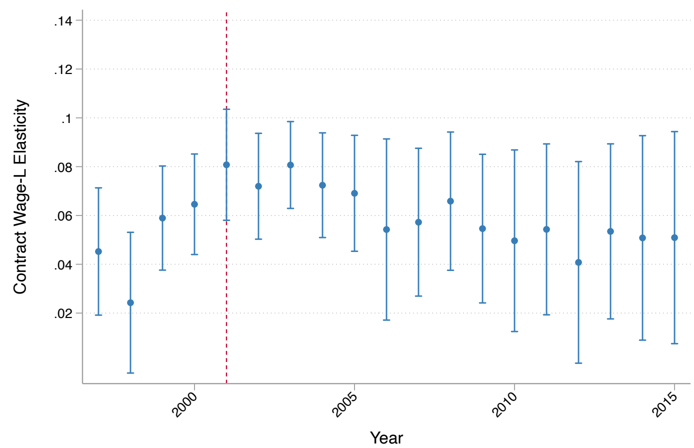
where L_{it} is the number of workers. Panel (c) of Figure 10 plots β_t^{Size} from this regression which capture the extent to which the wage differential between contract and permanent workers varies

Figure 10: Contract and Permanent Relative Wages and Plant Size Over Time

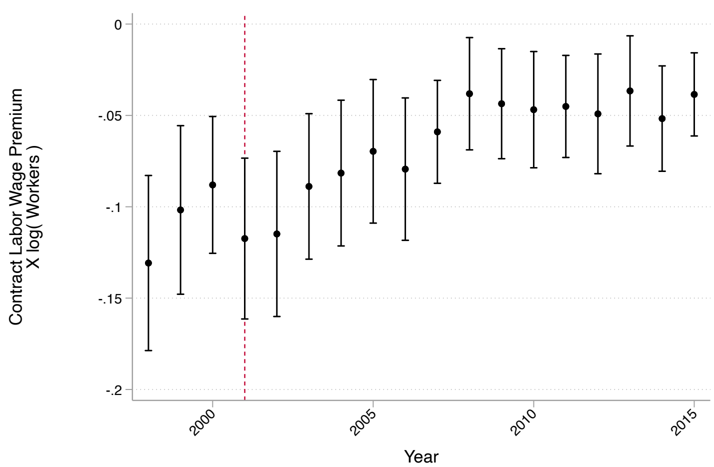
(a) Contract Relative Wage and Plant Size, Raw



(b) Contract Relative Wage and Plant Size, Residualized



(c) Relative Contract Labor Wage-Plant Size Elasticity Over Time



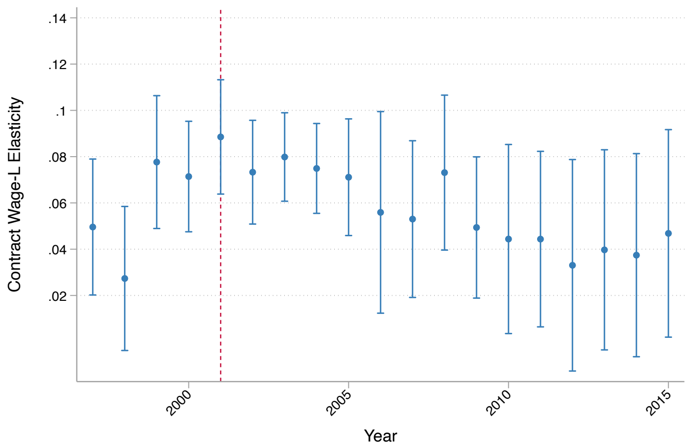
Note: In panel (a), we consider plants which hire contract workers and and plot the non-parametric relationship between plant-size and the log relative average wage per worker between contract and permanent workers. In panel (b), we repeat the exercise but first regress the log relative average wage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

with the number of workers employed at the establishment. While our data only allow us to examine this relationship from 1998 onwards, it appears that the fall in the wage premia of permanent workers within large plants began around or just after the SAIL adjudication.

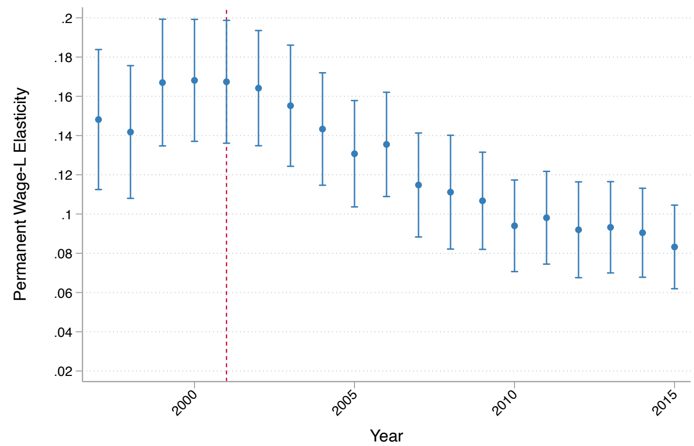
Did Permanent Labor Become Cheaper for Large Plants? Figure 10 suggests that the cost of permanent workers relative to contractors fell for larger plants during the 2000s. In Figure 11, we diagnose whether this was driven by an increase in contract wages or a fall in permanent wages at larger plants during the 2000s. Panel (a) plots the elasticity over time of the average wage per contract worker to the number of 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 elasticity rises and then falls slightly around the SAIL event, but the magnitude of the change is relatively small.

Figure 11: Contract and Permanent Wages and Plant Size Over Time

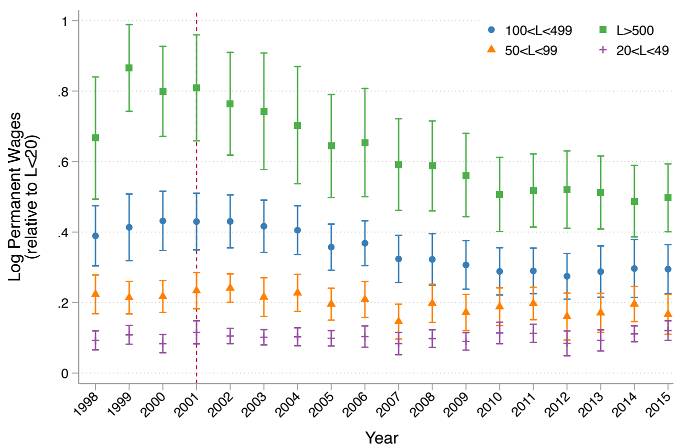
(a) Contract Wage - Employment Elasticity Over Time



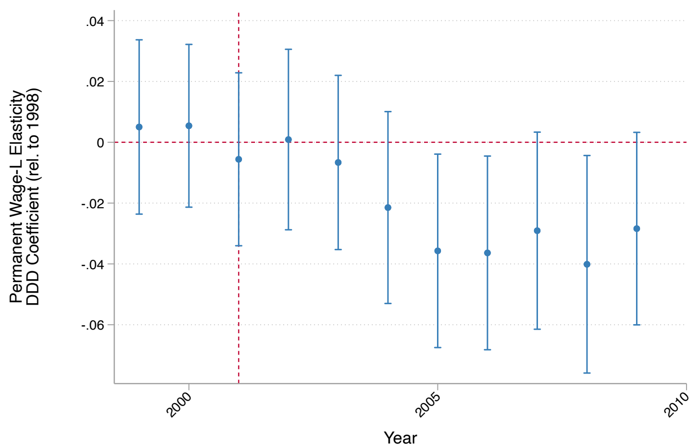
(b) Permanent Wage - Employment Elasticity Over Time



(c) Permanent Worker Wages by Size



(d) 1990 Staffing and the Permanent Wage Elasticity



Note: In panel (a) we regress the log average contract wage on log plant number of 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 permanent workers. Panel (c) examines the relationship less parametrically by looking at average wages paid to permanent workers by plants with different numbers of employees. Panel (d) regresses log average wage of permanent workers on a full interaction of log 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 permanent 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 (d) ends then. In Panels (a)-(c) standard errors are clustered by industry, while in Panel (d) they are clustered by district (since the 1990 staffing variation is at the district-level).

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 workers. Here, we observe a pronounced drop post-SAIL. Permanent workers became disproportionately cheaper for large plants starting in 2001. While our wage data by worker category only begins in 1998, the lack of a pre-trend in the wage elasticity in Figure 9 suggests the permanent wage elasticity was likely constant prior to 1998 given the dominance of permanent vis-a-vis contract workers during those early years. Panel (c) runs a less parametric regression to examine how average wages paid to permanent workers by plants with different numbers of employees changed over time. Relative to small plants with less than 49 workers, we see some convergence in permanent wages after the SAIL decision.

Overall, panels (a) to (c) of Figure 11 suggest that the rise in the relative cost of contract workers amongst large plants documented in Figure 10 was driven by a fall in the cost of permanent workers rather than a rise in the cost of contract workers. Panels (b) and (c) suggest that this change lines up fairly closely with the SAIL decision.

Panel (d) in Figure 11 examines how the relationship between the elasticity of permanent wages to employment and a district's level of staffing in 1990 evolved over time. If the SAIL decision was the principal factor driving the downward trend in this elasticity during the 2000s, then we expect that districts with more staffing available (in 1990) should experience a larger decline after 2001. To test this, we regress log wage of permanent workers on a full interaction of log 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 estimated triple interaction terms in this difference-in-difference-in-difference regression, interpreted as the change in the permanent wage plant size elasticity in a given year for a 1% increase in the 1990 staffing measure, relative to the omitted category of 1998, are reported in panel (d). They are mostly negative post-SAIL, consistent with the permanent worker wage-plant size elasticity falling more in districts with greater exposure to staffing in 1990.

In Appendix Section E.9, we use CPHS data to assess whether the patterns in Figure 11 could be explained by increased negative selection of permanent workers when the contract labor share increases. We find that if anything, the selection looks positive, with permanent workers being somewhat older and slightly more educated as the contract labor share in their industry increases.

7 A Model of Establishment Growth, Innovation, and Firing Costs

The empirical evidence suggests that the increased use of contract labor is likely due to an increase in the supply of contract workers rather than higher demand for such workers. Furthermore, the evidence also suggests that plants that choose to employ more contract labor do so because it reduces future labor adjustment costs. Lastly, the evidence also suggests that the increased availability of contract labor allowed large plants to grow.

In this section, we use a model to quantify the effect of the IDA, and of the expansion of contract labor in the presence of the IDA, on aggregate TFP. If all we were interested in is the static output loss from the misallocation of labor due to the IDA, then the model in section 4 where the probability a firm's product is destroyed is an exogenous parameter will suffice.

However, we also want to know the effect of the expansion of contract labor on the growth rate by changing the incentives to innovate. To do this, we extend the model in Section 4 by endogenizing the innovation rate. We assume innovation takes the form of improving the quality of another firm's product. Therefore, the probability a firm's product is destroyed is endogenous to the innovation rate. It is possible that innovation also takes the form of new products or quality improvements in the firm's own products. However, these alternative models of innovation can not generate the negative shocks that are essential for the IDA to have empirical bite. The reason is that innovation in the form of new products or own quality improvements raises the wage but otherwise have no negative implications for incumbents that do not innovate.

Finally, to capture the fact that higher use of contract labor is associated with a decline in the average product of labor among the plants that increase their use of contract labor, we assume that the expansion of contract labor is driven by a reduction in the fixed cost of using contract labor F. We then use the model to assess the effect of a decline in F on static misallocation and on the aggregate innovation rate by changing the innovation incentives of high-type establishments.

7.1 A Model of Endogenous Innovation

When an establishment 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* 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 establishment and ξ_H is the productivity of the high-type establishment in R&D. The cost of innovation for the low-type establishment is given by a similar expression, with x_H and ξ_H replaced by x_L and ξ_L.

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 establishment x_H is:

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

where v_H is the normalized value of a variety of a high-type plants and $\hat{q}_j$ is the normalized quality of a product q_j.[46] The optimal innovation rate for a low-type establishment x_L is given by the same expression with v_H and ξ_H replaced by v_L and ξ_L. Holding the expected value of a variety constant, $\xi_H > \xi_L$ implies that the innovation rate of high-type plants is higher than that of low-type plants.

Turning to entrants, their cost of innovation is $(x_E/\xi_E)^{\frac{1}{1-\beta}} Y$ 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 establishment. 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 establishment. Equating the cost to the benefit, the optimal innovation rate for an entrant is given by:

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

The innovation rate of entrants is increasing in the productivity of entrants in R&D and in the weighted average of the value of a variety for a high- and low-type establishment.

The key endogenous variables in the innovation rates in equations 7.1 and 7.1 are the expected value of a variety for high- and low-type plants. For a low-type establishment, the expected value of a variety is given by a standard arbitrage equation:

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

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 is the expected value from innovating and possibly grabbing another variety.

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

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

where $\mathbb{P}(\hat{q} > \hat{q}^*)$ denotes the probability that the normalized quality of the innovated variety exceeds the normalized threshold quality, $\tilde{t}\left(\hat{q}\right) = g^{-1}\left[\ln(\hat{q}) - \ln(\hat{q}^*)\right]$ denotes the duration for which the normalized quality of the innovated variety remains above the normalized threshold quality.[47]

The expected value of a variety for a high type establishment can be interpreted as follows. The first line is the expected flow of 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 establishment because of the possibility it will be forced to hire too few permanent workers due to the firing cost. The value is adjusted for the length

[46] Both are normalized by aggregate output per worker. Also $\tilde{\beta} \equiv (1-\beta)^{\frac{1-\beta}{\beta}}$.

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

of time $\tilde{t}$ the establishment 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 plants and the aggregate rate of innovation is then pinned down by the rates of innovation. Specifically, the share of products owned by high type plants ϕ in a steady state is:

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

The steady state share of high-type plants is increasing in x_H and decreasing in x_L. The aggregate rate of innovation is then given by the innovation rates of each type of plant, x_H and x_L, and the shares of each type of plant, ϕ and $1-\phi$:

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

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 by:

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

which is the product of the innovation rate x and the average step size $\frac{1}{\theta-(\sigma-1)}$ adjusted by $\frac{1}{1-\psi}$.

7.2 Parameter Estimates

The model is characterized by 10 parameters: $\{\rho, \sigma, \beta, \alpha, \kappa, \xi_H, \xi_L, \xi_E, \theta, F\}$. We impose values for ρ, β, and σ and estimate the remaining parameters in three steps.[48]

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 8. The innovation rates for high- and low-type plants x_H and x_L are jointly identified by the job creation rate by incumbents and the 75th percentile of the establishment 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 plants. The 75th percentile of the establishment 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 plants 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.

[48] We pick $\beta = 0.5$ to match the elasticity of successful innovation with respect to R&D. In addition, we assume the elasticity of substitution across products $\sigma = 2$ (which implies a markup of 50%), a discount rate $\rho = 0.05$, and a reflecting barrier parameter $\psi = 0.02$. These numbers are standard; see for example Acemoglu et al. (2018) and the references therein.

To identify the firing costs and contract labor adoption costs, we target the elasticity of value-added per wage-bill with respect to the establishment's wage-bill and the share of large plants using contract labor intensively. We use the wage-bill instead of employment to account for differences in labor quality across plants, including differences in labor quality between contract and permanent workers. Since the ratio of average revenue products of labor between plants employing and not employing contract labor is $1 + x\kappa$ 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 plants adopt contract labor. The share of high type plants among entrants α is pinned down by the difference in exit rates between young and old plants conditional on establishment size. Due to selection, the pool of older plants will contain more high-type plants, and so a higher α manifests itself through more high-type plants amongst old plants 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 7.1.[49]

Table 8: Moments in Model and Data

Moments	Parameter Identified	Period	Data	Model
Rate of Job Creation by Incumbents	$x_H + x_L$	Pre	0.0434	0.0526
Share of Employments in Entrants	x_E	Pre	0.0456	0.0365
Difference in Exit Rates, Young vs. Old	α	Pre	0.0132	0.0134
VA/Wage-Bill vs Wage-Bill Elasticity	κ	Pre	0.0444	0.0408
Pre-Period, % Large plants with Intensive Contract Labor Use	F^{Pre}	Pre	0.20	0.22
Post-Period, % Large plants with Intensive Contract Labor Use	F^{Post}	Post	0.37	0.36
75th Percentile of Establishment Age	x_H/x_L	Pre	21.00	15.95
TFP Growth	θ	Pre	1.0740	1.0695

Note: Table shows averages over 1999-2001 (pre-period) and 2013-2015 (post-period), unless otherwise noted, and includes plants with more than 5 workers. Job creation by incumbents is sum over incumbent plants with increasing employment in each one-year period divided by average of employment in the initial and final year. Share of employment of entrants in year t is employment of plants in year t that did not exist in year t-1 as a share of total employment in year t. Young plants are those with age < 10 and old plants are those with age > 10. Exit rate for young vs. old plants is computed by regressing an indicator variable for exit over one year dummies for young and old, establishment employment), and state-year and industry-year fixed effects. The VA/Wage-Bill vs Wage-Bill elasticity is computed by regressing log VA/Wage-Bill on log Wage-Bill. Intensive contract labor use defined as hiring more than 50% of workers through contractors. Large defined as more than 100 workers. TFP growth for manufacturing plants over 1993-2007, taken from Bollard, Klenow, and Sharma (2013).

The top panel in Table 9 shows the values of $\{x_H, x_L, x_E, \alpha, \kappa, F, \theta\}$ that most closely match these moments. High-type plants are much more innovative than low-type plants (which conduct almost

[49] 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.

no innovation) and about 6.3 times as innovative as entrants. There are many more low-type plants than high-type plants in the economy, with only around 2.6% of entrants likely to be high-type. 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 9: 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 plants among entrants	0.0255
κ	Firing cost of permanent 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

In the second step, we invert the expressions for optimal innovation decisions (given by equation 7.1 for incumbents and by equation 7.1 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 9. The second panel in Table 9 shows the resulting productivity parameters in R&D of the high-type and low-type plants as well as the entrants. The productivity of high-type plants in R&D is about 2.6 times higher than the productivity of entrants and 93 times larger than the productivity of low-type plants 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 plants that use contract labor intensively after 2000. Specifically, in the post-period we assume the innovation parameters ξ_H, ξ_L, ξ_E remain fixed and choose the change in F that most closely matches the share of large plants that use contract labor intensively by the end of the 2000s.[50] The third panel in Table 9 shows that to "explain" an increase from 20% to 37% in the share of labor plants that use contract labor intensively, the fixed cost of contract labor must have fallen from 1.21 to 0.65 (in units of the final good) over this period.

[50]See Appendix G for the simulation algorithm. We also keep fixed α, κ, and θ.

7.3 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 9 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 use using amongst large plants by 2015, this counterfactual allows us to quantify what Indian manufacturing would look like had only this change occurred over the fifteen year period.

Table 10 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 plants.[51]

Table 10: 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 (1999-2001) from Table 8. The third and fourth columns present the data and model-generated moments for the post-period (2013-2015), where the model-generated values are based on the estimated fall in F presented in Table 9. 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 shows that as more large, high-type plants hire contract labor in response to lower adoption costs, the elasticity of the average product of labor with respect to establishment size falls by 56%. This is close to the reduction of 50% observed in the data during the 2000s.

Row 2 shows that the employment share or job creation of entrants falls by 17% in response to lower contract labor adoption costs. In the data the employment share of entrants falls by 11%. As more high-type plants 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 plants falls as their products are more likely to be stolen, and the real wage rises due to increased labor demand by high-type plants. Since most entrants expect to enter as low-type plants (due to the low value of α), the entry rate declines.

The last row 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 of 7%. Table 11 shows why. The reduction in expected labor costs for large, high-type plants causes their distribution to fan out, with the largest plants growing by more as they accumulate new products (first row). As a result,

[51] None of these moments are targeted in estimation.

more creative destruction takes place across products within plants rather than across plants. 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 establishment-level creative destruction observed in the data but now in the same direction.

Table 11: Size of High-type plants and Product-Level Job Creation

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

Note: Table presents i) the ratio of 90/10 percentiles of size (measured by employment) for high-type plants 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 defined as the sum of changes in employment at product lines where incumbent plants innovated, normalized by the average employment across both periods. For each moment, the first column presents the value in the pre-period (1999-2001), the second that in the post-period (2013-2015), and the last the percent change over the two periods.

We now discuss the aggregate effects of reducing the fixed cost of contract workers. First, as calculated through the lens of the model, the static gain in aggregate output from the reallocation of labor towards high-type firms is 7.6%. Aggregate consumption rises by 5.0%, and the difference between output and consumption are the change in resources spent on R&D and the fixed costs spent on employing contract workers.

Another channel through which the reduced 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.

Table 12 shows why. The table decomposes the aggregate innovation rate (equation 1) into the contribution of innovation from high type plants, low type plants, and entrants in the pre (1999-2001) and post (2013-2015) periods. The rise in innovation by high-type plants (column 2) is almost exactly offset by a reduction in innovation by entrants (column 4), leaving the aggregate innovation rate (column 1) virtually unchanged. While large, high-type plants 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.

Table 12: Decomposition of Aggregate Innovation Rate

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

Note: Table shows decomposition of the aggregate innovation rate $x = \phi x_H + (1-\phi)x_L + x_E$ into innovation by high type plants ϕx_H, by low type plants $(1-\phi)x_L$, and entrants x_E. Pre-period is 1999-2001; post period is 2013-2015.

8 Implications of the Rise of the Staffing Industry for Workers

The model in the last section suggests that the rise in contract labor may have increased aggregate TFP, and thus, the average wage. In this section, we explore the effect of the increase in contract labor on the *distribution* of wages between workers.

We begin by showing wages associated with contract work compared to other employment arrangements. We use the CPHS sample, but this time expand the sample to include workers in informal plants as well as daily wage workers and self-employed.[52] Appendix Table E.15 shows regressions of log earnings on employment type in this sample in 2017, separately by education group ($<$ 10, $10-12$, and >12 years of schooling). Across all education groups, all employment arrangements vastly dominate daily-wage/casual employment (the omitted category). Informal contract work is associated with the second-worst outcomes for workers.

Appendix Table E.16 shows the share of workers in each employment status. The two worst employment arrangements in terms of worker's earnings, daily wage employment and informal sector contracting, are by far the most common in Indian manufacturing, with 23% of manufacturing workers in India being daily-wage workers and another 26% being temporary workers in the informal sector. Less educated workers are particularly over-represented in these lower-paying employment arrangements, with 37% of workers with less 10 years of schooling in daily wage employment. Hence, the growth of the contracting model in formal manufacturing has the potential to add better opportunities to workers stuck in worse employment arrangements.

Table E.17 exploits the panel characteristics of the CPHS to calculate year-to-year transitions between employment categories. We broaden the CPHS sample to include workers outside of manufacturing as well as the non-employed.[53] The high transition rate into permanent employment for workers that are employed as formal contract workers is notable. Remember that these are the work-

[52]See Appendix C for details.

[53]We calculate transition rates between employment arrangement over a year in 3 waves of the CPHS data (May - Aug 17, Sep - Dec 17, Jan - Apr 18). Table E.17 shows the average transition rate across the three waves.

ers likely to be supplied by the staffing companies that expanded after the late 1990s. Conditional on formal contract work, the transition rate into permanent employment is 32%, which is the highest transition rate into permanent employment among all employment arrangements. This evidence suggests that an important "effect" of accessing formal contract employment is that it increases the probability of permanent work.

Motivated by this evidence, we sketch a model to estimate the equilibrium effect of the increased availability of contract labor on workers with different skill sets. We assume that a worker is characterized by their group g and labor market status s. Empirically we measure labor market status s as permanent, daily wage, self-employed, temporary with provident fund, and temporary without provident fund, and worker type g as years of schooling ($<$ 10, 10-12, and $>$ 12). In addition, to match the fact that workers switch between labor market status, we assume that labor market status is a choice variable. Intuitively, the lifetime utility from a specific labor market status is not simply the wage from being in that status but also its "effect" on the probability of transitioning into other labor market statuses.

Specifically, the utility of a worker of type g and labor market status s in the current period from switching to labor market r in a future period is $\frac{w_{rg}\,\epsilon_r}{dsr}$ where w_{rg} is the wage, d_{sr} is the cost of switching from s to r, and ϵ_r is the worker's idiosyncratic preference for sector r.

We then "explain" transitions in labor market status by assuming that a worker gets a new draw of ϵ (for each of the labor market states) in each period. Assuming that ϵ follows a Fréchet distribution with shape parameter θ, the probability that a worker of type g in labor market status s switches to labor market status r is given by:

$$P_{rsg} = \frac{\left(\frac{w_{rg}}{dsr}\right)^{\theta}}{\sum_k \left(\frac{w_{kg}}{d_{sk}}\right)^{\theta}} \tag{2}$$

The steady-state share of workers of group g in each labor market status l_{rg} is then given by:

$$\{l_{rg}\} = \{P_{rsg}\}'\{l_{rg}\} \tag{3}$$

Average lifetime utility of a worker of group g is then given by:[54]

$$V_g = \sum_s l_{sg} \left(\sum_k \left(\frac{w_{kg}}{d_{sk}} \right)^{\theta} \right)^{1/\theta} \tag{4}$$

Average lifetime utility is a weighted average of the utility associated with each labor market state $\left(\sum_k \left(\frac{w_{kg}}{d_{sk}} \right)^{\theta} \right)^{1/\theta}$ where the weights are the steady-state share of workers in each state l_{rg}.

We then estimate the effect of the expansion of contract labor between 1999 and 2017 on the lifetime utility of each group in three steps.

First, we use CPHS data to calculate the transition matrices P_{rsg} and the wage w_{rg} in 2017. These

[54] We assume no discounting of future income for simplicity.

two data moments are calculated for the three schooling groups and for all individuals over age 15 in all sectors. Then, assuming the cost of staying in the same labor market status is zero ($d_{rr} = 1$), we use equation (2) to infer the transition cost d_{sr} from the ratio of the transition probability from r to s to the transition probability of staying in r.[55]

Second, we assume the wage of contract workers changes between 1999 and 2017 uniformly for all worker groups g. For this exercise, we assume that wages for all the other labor market states other than contract labor and the transition costs d_{rg} are unchanged at their 2017 levels. That is, $\Delta w_{rg} = \gamma_r$ where r are contract workers and $\gamma_s = 1$ for $s \neq r$. We then choose γ_r such that the change in the steady-state share of contract workers in the model is equal to the change observed in the data for formal manufacturing workers between 1999-2000 and 2017.[56]

Third, we impute the steady-state labor shares $\tilde{l}_{rg}$ implied by γ_g we calculated in the previous step using equations (2) and (3). We then calculate expected lifetime welfare in 1999 from equation (4) where l_{rg} is replaced by $\tilde{l}_{rg}$, the wage of contract workers is replaced by w_{rg}/γ_r, and d_{rg} and the wage in other sectors are held fixed.

Table 13: Lifetime Utility and Self-Employment Share by Schooling Groups

Schooling Group	Lifetime Utility 1999	Lifetime Utility 2017	% Self-Employed 1999	% Self-Employed 2017
$<$ 10 Years	1	1.05	10.8%	7.6%
$10 - 12$ Years	1.22	1.28	10.6%	7.0%
$>$ 12 Years	1.57	1.73	16.7%	13.3%

Note: We assume the only change in 1999 relative to 2017 is the wage from contract work. Columns 1 and 2 show the PDV of lifetime utility in 1999 and 2017 computed from equations (2), (3), and (4). Lifetime utility is normalized by utility in 1999 for workers with $<$ 10 years of schooling. Columns 3 and 4 show the share of workers in each schooling group that are self-employed in 1999 and 2017 computed from equations (2) and (3).

Table 13 shows the results of this calculation. The first column shows average lifetime utility of each schooling group in 1999 relative to workers with $<$ 10 years of schooling. Not surprisingly, average utility is increasing with schooling. The second column shows average utility in 2017 after the expansion of contract labor. The largest increase in utility is for the most educated group ($>$ 12 years), the next largest is for the least educated group ($<$ 10 years), and the smallest increase is workers with $10 - 12$ years of schooling.

We next show the model's estimate of the effect of the expansion of contract labor on the share

[55]We also use CPHS data on the wage of each worker type by labor market status w_{rg}. We assume $\theta = 3$.

[56]The share of formal manufacturing workers increased by 13.8 percentage points between 1999-2000 and 2017, as calculated in the sample of formal workers in the ASI in 1990-2000 and the CPHS in 2017. The total share of workers with labor market status r in steady-state is given by $l_r = \sum_g l_{rg}$ where l_{rg} is given by equations (2) and (3).

of workers that choose self-employment (in columns 3 and 4). The self-employment share declines for all three schooling groups, roughly equally for all educational groups. Since it is likely that the vast majority of the self-employed are the owners of what the model calls "low-type" firms, this calculation suggests that the expansion of contract labor also resulted in a decline in the number of such firms. This prediction is consistent with the fact shown earlier (in Table 10) that the employment share of entrants declined over the period when contract labor expanded.

9 Conclusion

We provide evidence that the employment restrictions on large Indian plants appear 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 plants. The use of contract labor allows large Indian plants to respond to shocks to profitability, expand employment, and invest in new products. This shows up as an increase in the thickness of the right tail of the establishment size distribution in India and a decrease in the average product of labor of large Indian plants. 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 from large incumbent plants. In the data, this is consistent with a decline in the employment share of entrants. The decline in innovation among entrants entirely offsets the increased innovation by incumbents, so there is no net increase in innovation.

Despite the decline in the average product of labor seen in the data since the early 2000s, it is still the case that the average product of labor in large Indian plants is substantially higher than that of smaller plants, and that Indian manufacturing is still dominated by a large number of small informal plants. This suggests that a greater reliance on contract labor is only a partial answer to the constraints faced by formal manufacturing in India. It is also possible that the reliance on contract labor can lead to longer term problems for Indian manufacturing.

Finally, we made an attempt to quantify the distributional effects of contract employment, but our answer should be viewed as preliminary. For example, our estimation takes as given the transition matrices between the different employment arrangements, but it it is possible that they are endogenous to the aggregate magnitude of contract employment.

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A Appendix Tables

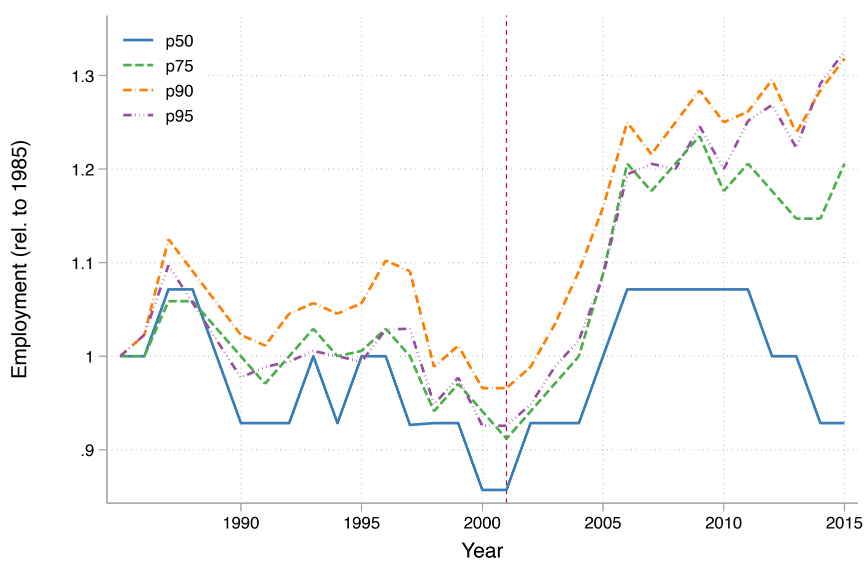
Table A.1: Staffing Heterogeneity: Robustness to Alternative Decay Rates

	(1)	(2)	(3)
log Employment	0.046***	0.052**	0.037**
	(0.017)	(0.020)	(0.014)
log VA/Worker	-0.020	-0.013	-0.021
	(0.017)	(0.020)	(0.014)
log VA/Wage-Bill	-0.041***	-0.048***	-0.033***
	(0.013)	(0.017)	(0.011)
log VA/Effective Worker	-0.020	-0.008	-0.023*
	(0.017)	(0.020)	(0.014)
Decay Parameter	0.0075	0.005	0.01
Wght Emp X Year FE	X	X	X
Establishment Controls X Year FE	X	X	X
Dist Controls X Year FE	X	X	X

This table replicates the last column of Table 4 for alternative values of the decay rate κ.* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

B Appendix Figures

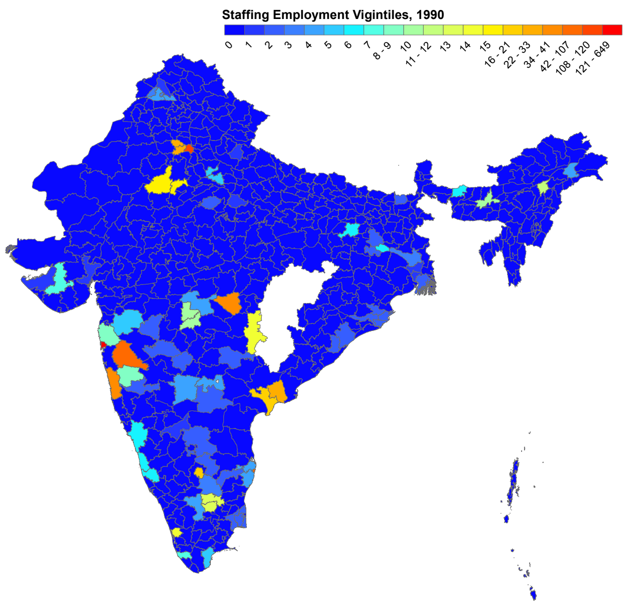
Figure B.1: Manufacturing Plant Size Distribution Over Time in the ASI



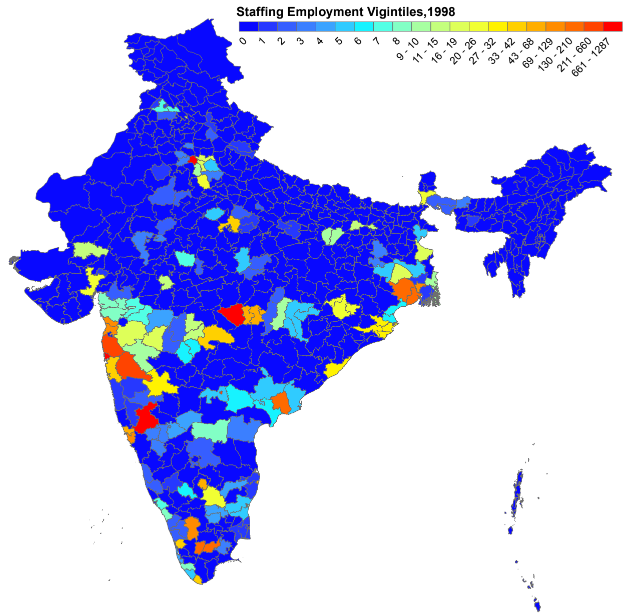
Note: Plot shows percentiles of plant employment in manufacturing from the ASI.

Figure B.2: Spatial Expansion of Staffing Industry

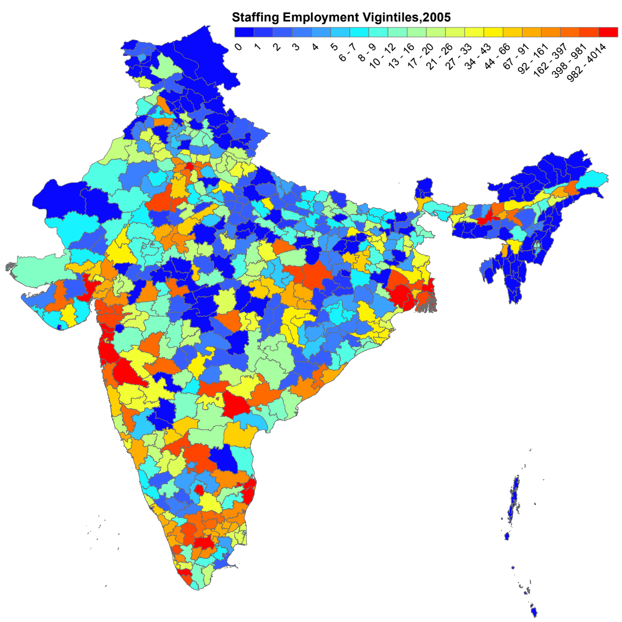
(a) 1990



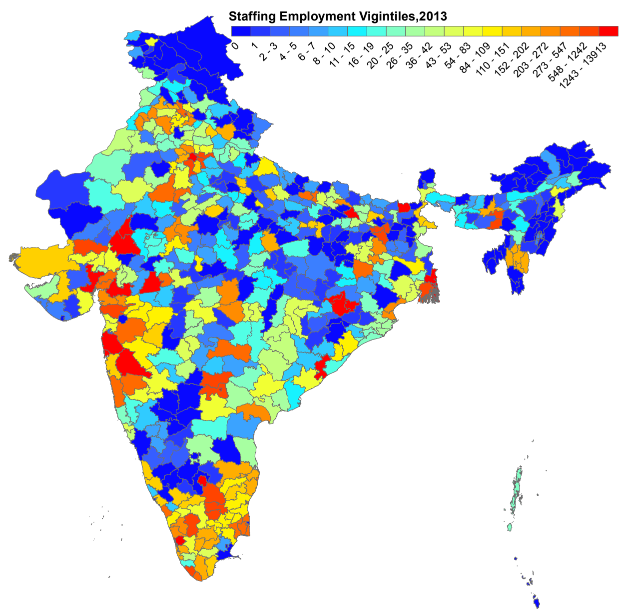
(b) 1998



(c) 2005



(d) 2013

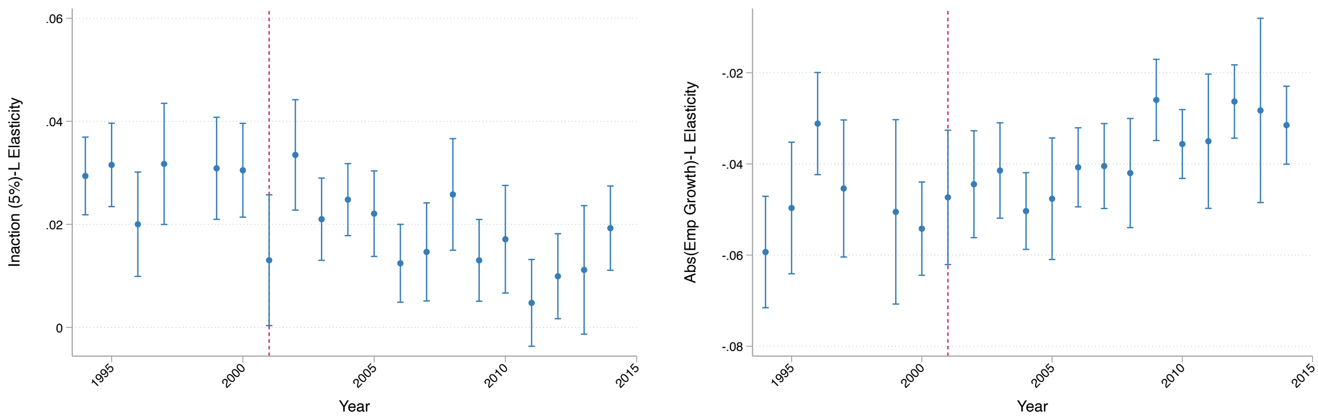


Note: Data is from the Economic Census. Jammu and Kashmir and parts of Madhya Pradesh missing in 1990 census.

Figure B.3: Alternative Measures of Inaction and Employment Growth vs Size Elasticities

(a) Inaction (5%) - Size Elasticity

(b) Absolute Value of Emp Growth - Size Elasticity



Note: Figure repeats Panel (a) of Figure 6 for alternative outcome measures. Panel (a) defines Inaction using a 5% cutoff rather than the 10% used in the main text. Panel (b) uses the absolute value of employment growth as the outcome.

C Consumer Pyramids Household Survey: Sample Construction

The Center for Monitoring the Indian Economy (CMIE)'s Consumer Pyramids Household Survey (CPHS) is a panel survey of about 160,000 households across India. CPHS surveys are carried out in a "wave" of 4-months, where each household (and its members) is attempted to be surveyed during the 4-month period; thus, a household is attempted to be surveyed 3 times a year with about a 4-month gap between each visit. The first wave of CPHS took place in January 2014. CPHS provides both weights and adjustment factors, the product of which we use to make each wave representative of the Indian population over 15 years of age.

CPHS allows us to identify individuals employed in manufacturing based on its "industry of occupation" variable. We create a concordance between the industry code in the CPHS and the NIC-based industry code in the ASI. In addition, to zoom in on non-managerial workers ("workmen"), we use CPHS's "nature of occupation" and exclude any individual classified as "manager" under this variable.

Starting with the May-Aug 2017 wave, CPHS started asking employed individuals about their "employment arrangement," offering a menu of 4 possible options: 1. salaried - permanent; 2. salaried - temporary; 3. daily wage worker/ casual labour; and 4. self-employed. This variable allows us to restrict the CPHS sample to permanent workers and temporary (contract) workers.

Unfortunately, CPHS does not contain information on employer registration status (e.g.,formal vs. informal) nor does it contain information on establishment size. With most of Indian's manufacturing employment happening outside of the formal sector, additional steps are required to improve the mapping between ASI plants and individuals in CPHS likely employed in those plants, as much of permanent and temporary employment in CPHS must be happening outside of the formal manufacturing sector.

Indeed, Table C.2 confirms that the number of non-managerial permanent and contract workers employed in manufacturing in CPHS in 2017 greatly exceeds the number of non-managerial permanent and contract workers in ASI in 2017.[57] Also, the share of contract workers in CPHS (54%) greatly exceeds that in ASI (35%).

Table C.2: Number of Workers and Contract Labor Share in Manufacturing: ASI vs. CPHS

	ASI	CPHS
All Workers		
# Permanent Workers	3,816	9,988
# Contract Workers	2,091	11,709
Contract Labor Share	35%	54%
Formal Workers		
# Permanent Workers	3,448	4,990
# Contract Workers	2,044	2,678
Contract Labor Share	37%	35%

Note: Table displays counts of permanent and contract workers (in thousands) and contract labor share in ASI and CPHS' manufacturing employment. Top panel includes all ASI non-managerial workers and restricts the CPHS sample to non-managerial permanent and temporary workers employed in the manufacturing sector. Bottom panel restricts ASI to non-managerial workers employed in plants with at least 20 non-managerial workers and CPHS to non-managerial permanent and temporary workers employed in the manufacturing sector with access to provident fund. Tabulations use sampling weights in the ASI and the CPHS. The data relies on the ASI conducted between April 2017 and March 2018 and the May-August 2017, Sept-Dec 2017, and January-April 2018 waves of the CPHS (we show the average of the three CPHS waves).

In order to make progress, we make use of the fact that formal plants (whether in the manufacturing or staffing sectors) with 20 workers or more are subject are subject to the Contract Labor Act (see Section 2) and the Provident Fund Act. In addition, the CPHS records whether or not a given worker has access to a provident fund so we use this variable as a proxy for employment in a formal plant.[58]

As seen in the second panel of Table C.2, when we restrict the ASI sample to plants with more than 20 workers and the CPHS to non-managerial permanent and contract workers in manufacturing and with access to provident funds, we see much greater similarity between the two datasets, both in terms of absolute numbers of permanent and contract workers, as well as the contract labor share, even though CPHS still appears to cover a greater number of workers than ASI (possibly because of

[57] 2017 is the earliest year of overlap between ASI and CPHS data that includes the "employment arrangement" variable.

[58] See https://www.epfindia.gov.in/site_docs/PDFs/Downloads_PDFs/EPFAct1952.pdf for details on the Provident Fund Act.

an imperfect overlap between industry definition between the datasets).

Therefore, in all tables that rely on the CPHS, except for those tables in Section 8 which extend the CPHS sample to workers outside of formal manufacturing, we restrict the CPHS sample to non-managerial permanent and temporary workers employed in manufacturing with access to provident fund. We do this because, as suggested by the bottom panel in Table C.2, this sample is a reasonably representative sample of ASI non-managerial workers.

Finally, starting in January 2018, CPHS develops a finer "occupation" variable. We use this variable in Table 1 to tabulate the 10 most common occupations among permanent and contract workers employed in the formal manufacturing sector, as defined above.

D Top and Bottom Industries by Contract Labor Use

Table D.3 shows the top 10 and bottom 10 industries in the 2013-2015 ASI as measured by the share of contract workers in total employment in the industry. Table D.4 shows the top 10 and bottom 10 industries as measured by the percentage point change in the share of contract workers in total employment in the industry between 1990-2001 and 2013-2015 in the ASI.

Table D.3: Top 10 Industries by Use of Contract Labor in 2013-15

	Top Industries		Bottom Industries	
Rank	Industry	CL Share	Industry	CL Share
1	Cement, lime and plaster	72%	Musical instruments	4%
2	Malt liquors and malt	54%	Knitted and crocheted fabrics	10%
3	Bicycles and invalid carriages	52%	Saw milling and planing of wood	11%
4	Other non-metallic mineral products	52%	Cordage, rope, twine and netting	11%
5	Industrial process control equipment	51%	Starches and starch products	11%
6	Distilling, rectifying and blending of spirits; ethyl alcohol	49%	Other textiles	12%
7	Paints, vanishes and similar coatings	48%	Other manufacturing	12%
8	Motorcycles (does not include repair)	47%	Aircraft and spacecraft	14%
9	Production and processing of meat and meat products	46%	Other transport equipment	14%
10	Pharmaceuticals, medicinal chemicals and botanical products	45%	Apparel (except fur)	16%

Note: Table shows the top 10 and bottom 10 industries as measured by the share of contract workers in total industry employment in the 2013-2015 ASI.

Table D.4: Top 10 Industries by Change in Use of Contract Labor between 1999-01 and 2013-15

	Top Industries		Bottom Industries	
Rank	Industry	Δ CL Share	Industry	Δ CL Share
1	Cement, lime and plaster	60%	Pesticides and other agro chemicals	-27%
2	Industrial process control equipment	43%	Processing of fish and fish products	-23%
3	Bicycles and invalid carriages	33%	Musical instruments	-19%
4	Motorcycles (does not include repair)	30%	Embroidery and zari work and making of ornaments	-7%
5	Builder's carpentry and joinery	30%	Starches and starch products	-6%
6	Plastic products	28%	Basic precious and non-ferrous metals	-5%
7	Pharmaceuticals, medicinal chemicals and botanical products	27%	Processing of fruit, vegetables and edible nuts	-5%
8	Office, accounting, and computing machinery	26%	Glass and glass products	-5%
9	Engines and turbines (except aircraft, vehicle and cycle engines)	26%	Footwear	-4%
10	Publishing of recorded media	26%	Made up textile articles (except apparel)	0%

Note: Table shows the top 10 and bottom 10 industries as measured by the percentage point change in the share of contract workers in total industry employment between the 1999-01 ASI and the 2013-2015 ASI.

E Additional Empirical Results

E.1 Single-Plant Firms

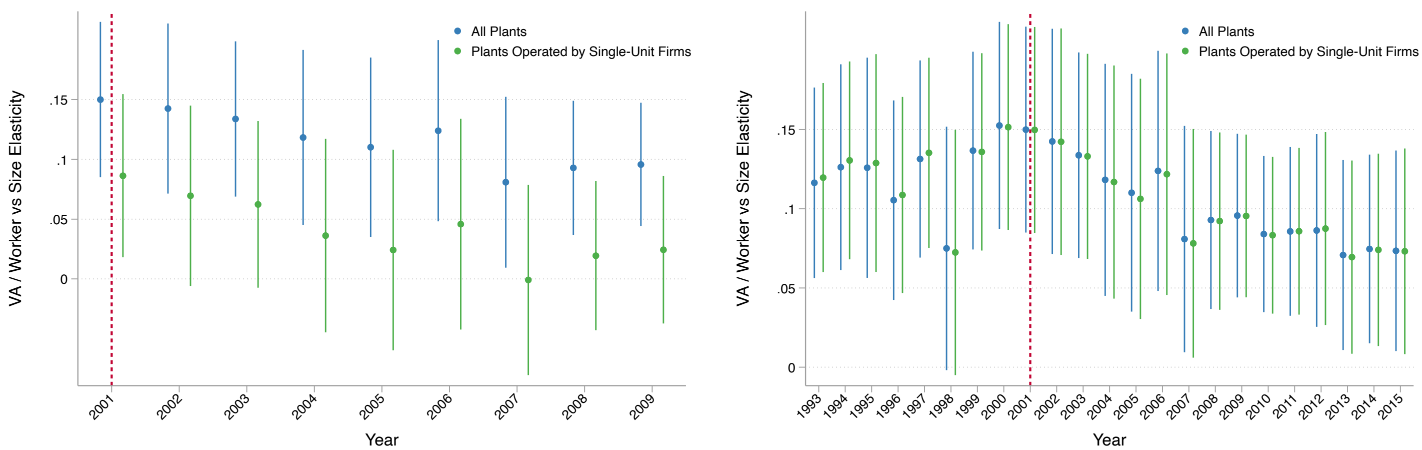
While the IDA applies to plants rather than firms, the ASI data only comes at the establishment-level and precludes us from measuring outcomes at the firm-level. To address the potential concern that changes in activity across plants within multi-plant firms could be driving our key empirical results, we recreate our main result on the time series of the VA/worker vs size elasticity for a sample of single-plant firms.

There are two ways to identify single-plant firms in the ASI. The first, which we refer to as "Measure 1," uses the variable which asks "How many total number of units the company has." This precisely measures whether a plant is owned by a single-plant firm, but it is only available between 2001 and 2009. We find 90.4% of plants are owned by single-plant firms according to this definition. The second, which we refer to as "Measure 2," uses the variable which asks the "Number of units for which the schedule is compiled." This will be one for single-plant firms, and may be one for multi-plant firms (e.g.,if they file a single survey response for a plant, they will report 1 here also). The measure is less precise in identifying single-plant firms, but it available between 1993 and 2015. According to this measure 99.4% of plants are owned by single-plant firms.

The results are shown in Figure E.4. We repeat the regression to determine the size elasticity in each year using the sample of single-plant firms using either measure, and plot it alongside the results from the main paper. Using the first measure in panel (a), we see the relative trends in the VA/worker vs size elasticity are identical over the nine years this variable is available. The point estimates are lower than those from the main sample, which is understandable given that we are excluding some of the largest plants (those which belong to multi-plant plants) from the analysis, although the two are statistically indistinguishable. Using measure 2 in panel (b), we see that the two series are essentially identical.

Figure E.4: VA/worker vs Size Elasticity: Plants Owned by Single-Plant Firms vs All Plants

(a) Measure 1 (b) Measure 2



Note: Plots recreate the baseline results and those produced when estimating the regression on the sample of single-plant firms. Measure 1 uses the variable in the ASI which asks "How many total number of units the company has." Measure 2 uses the variable which asks the "Number of units for which the schedule is compiled." See text in Section E.1 for details.

E.2 Potential Misreporting of Contract Employment

One potential concern is that data on contract labor use within plants may be misreported in the ASI. For example, if plants employ contract workers for core tasks in contravention of the Contract Labor Act they may be reticent to report these workers to the NSSO. Moreover, if the SAIL judgment relaxed these concerns then the uptick in contract labor use among large plants in the ASI during the 2000s may not be real at all.

We provide direct evidence against this by assessing whether electricity use and sales within plants respond differently to permanent and contract workers. Consider the relationship between electricity use and labor (analogous expressions apply when we replace electricity with sales). Suppose

Table E.5: Responsiveness of Electricity and Sales to Permanent and Contract Labor

	Log Electricity	Log Sales
Contract Labor Growth	0.324*** (0.021)	0.387*** (0.020)
Permanent Labor Growth	0.351*** (0.019)	0.396*** (0.019)
Contract Labor Growth x Post SAIL	-0.037** (0.018)	-0.027 (0.017)
Permanent Labor Growth x Post SAIL	-0.040** (0.016)	-0.018 (0.014)
p-val: row 1 = row 2	.009	.310
p-val: row 3 = row 4	.823	.321

Note: Observation is an establishment-year. Each entry corresponds to the coefficient from a regression where the outcomes are log electricity use (column 1) or log sales (column 2) on the dependent variables in the rows with establishment, state-year, and industry-year fixed effects. Contract Growth refers to a measure of contract labor growth defined as the plant's contract labor share in year t-1 x log contract labor in year t. permanent Labor Growth is defined in the same way. Both these independent variables are interacted with a post-SAIL dummy. P-value from the hypotheses tests of these 2 independent variables being equal is reported in the bottom rows of each panel. Data covers 1993-2015, excluding 1997 for electricity regression due to unreliable values for electricity usage. Standard errors clustered at the industry level. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

electricity use in plant i and year t depends on total employment through

$$E_{it} = F(\underbrace{L_{Fit} + L_{Cit}}_{L_{it}}),$$

that is contract and permanent workers affect electricity demand equally. A first order approximation yields

$$\ln \hat{E}_{it} \propto \pi_{Fit-1} \ln \hat{L}_{Fit} + \pi_{Cit-1} \ln \hat{L}_{Cit} + hot,$$

where π_{Fit-1} and π_{Cit-1} are the shares of permanent and contract labor in total employment and $\hat{x}_{it} = x_{it}/x_{it-1}$.[59] That is, if the change in electricity use to employment is the same for both types of workers, then we expect the coefficients in a regression of the growth in electricity use on the weighted growth in permanent employment and the weighted growth in contract labor employment to be equal. Moreover, if the relationship is unaffected by the SAIL judgment then these coefficients should be stable before and after the decision. The same applies to the relationships between the growth in sales and both types of labor.

Table E.5 shows the results of this regression, including establishment, industry-year and state-

[59]The constant of proportionality is the elasticity of electricity use to total employment $\frac{\partial \ln E}{\partial \ln L}$.

year fixed effects and clustering at the district-level.[60] We measure electricity use at the plant level as the sum of "electricity own generated" and "electricity purchased" reported in the ASI. The two predictions established above are borne out in the data. First, the responsiveness of both electricity and sales growth to permanent employment growth equals the responsiveness to contract labor growth. For sales the coefficients are statistically indistinguishable (p-value of 0.37 in the penultimate row). For electricity they are statistically different but not economically so (elasticities of 0.32 vs 0.35). Second, the second set of p-values show that there was no change in this relationship after the SAIL judgment.[61] This supports the notion that the change in electricity and sales when hiring an additional permanent worker equals the change when hiring an additional contract worker, and this relationship is stable before and after SAIL. This suggests misreporting of contract workers in the ASI does not appear to be present during our period of analysis.

E.3 Alternative Measures of Labor Inputs

The main results measure labor inputs using the number of workers, but this may not be accurate if contract and permanent workers supply different units of effective labor. This section attempts to adjust for the different amounts of effective labor supplied by each type of worker using two approaches. First, we proxy effective labor inputs as $\tilde{L}_i = L_{Pi} + \bar{w}L_{Ci}$, where L_{Pi} and L_{Ci} are plant i's permanent and contract workers and $\bar{w}$ is the relative payment to contract workers (inclusive of wages, bonuses and benefits) in 1998. We fix $\bar{w}$ to its value from 1998 since payments to labor disaggregated by type are only provided from 1998 onwards, so this allows a longer series before SAIL. We note this adjustment would deliver a correct measure of effective labor only in the case where each worker type is paid their marginal product. When part of permanent worker wages captures rents, this provides an upper bound on the gap in effective labor supplied by contract workers. Second, we use the plant's total (non-managerial) wage bill to proxy effective labor inputs, which has the advantage that this is available for a greater number of years.[62]

Figure E.5 shows the VA / Size vs Size elasticity over time when measuring plant size using effective labor (panel a) or the wage bill (panel b). The same qualitative pattern emerges: the relationship between the average product and plant size rises during the 1990s and breaks from this trend in the 2000s, although the break is perhaps less stark than with the baseline measure.

Tables E.6 and E.7 repeat the specifications from Tables 4 and 5 respectively. In Table E.6, the reduction in value added over the wage bill after SAIL in districts with more 1990 staffing is both larger and more precise than when measuring labor inputs using the number of workers in Table E.6.

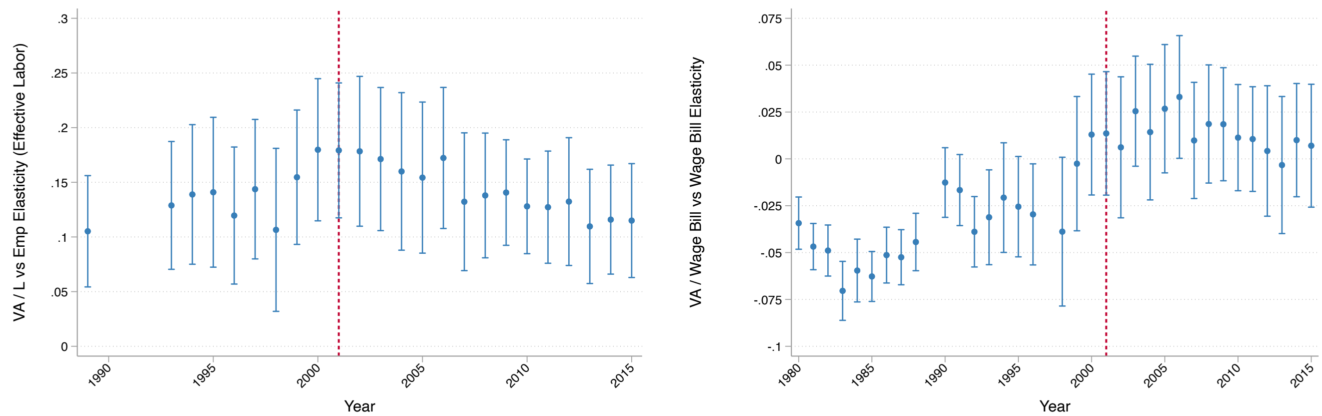
[60] We exclude electricity observations from 1997 - Mean and total electricity values are less than half of 1996 and 1998, suggestive of anomalies when collecting this data.

[61] For electricity, both elasticities fall slightly but by an equal amount.

[62] Formally, we define the wage bill as total labor costs (wages, bonuses, and benefits).

Figure E.5: Average Product of Labor vs Size Elasticities

(a) Effective Units of Labor (b) Wage Bill



However the results are similarly imprecise for value added per effective worker as in the main text. The results for E.7 are qualitatively unchanged from Table 5 for either alternative measure of labor inputs.

Table E.6: Heterogeneous Outcome Growth Post-SAIL by 1990 Staffing: VA / Wage Bill

	(1)	(2)	(3)	(4)	(5)	(6)
log VA/Wage-Bill	-0.027***	-0.028**	-0.029***	-0.026**	-0.041***	-0.050*
	(0.010)	(0.012)	(0.011)	(0.012)	(0.013)	(0.029)
N Obs.	453,165	453,165	443,847	421,484	421,484	421,186
N Clusters	435	435	435	367	367	367
log VA/Effective Worker	-0.017	-0.020	-0.021	-0.013	-0.020	-0.056*
	(0.012)	(0.016)	(0.013)	(0.014)	(0.017)	(0.032)
N Obs.	450,550	450,550	441,122	418,967	418,967	418,967
N Clusters	436	436	436	367	367	367
State × Year FE	X	X	X	X	X	X
Industry × Year FE	X	X	X	X	X	X
Wght Man Emp × Year FE		X	X	X	X	X
Establishment Controls × Year FE			X	X	X	X
Basic Dist Controls v Year FE				X	X	X
Wght Serv Emp × Year FE					X	X
District Emp Share Wghts						X

Note: Table corresponds to the same specification as Table 4 with VA / Wage Bill and VA / Effective Worker as the outcome..* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

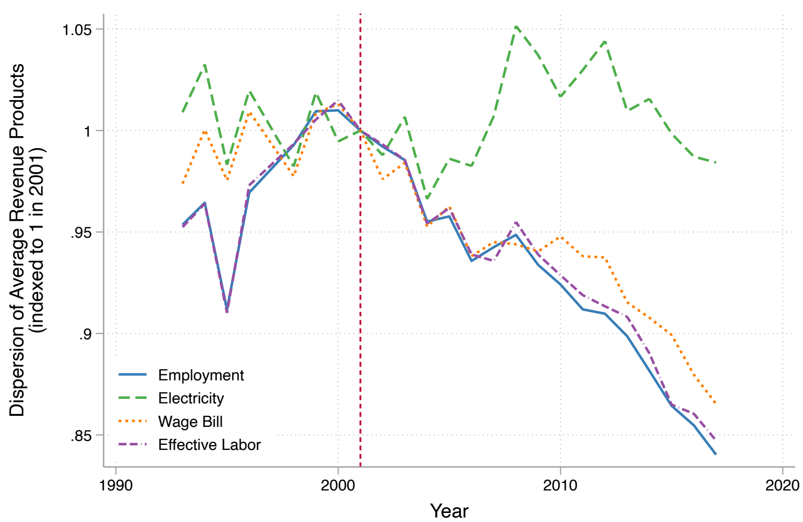
Table E.7: Correlates of Contract Labor Hiring Within Plants

	VA/Wage-Bill	VA/Effective Worker
Contract	-0.134***	-0.211***
	(0.009)	(0.015)
Contract $> 50\%$	-0.142***	-0.221***
	(0.009)	(0.026)

Note: Table corresponds to the same specification as Table 5 with alternative VA/Worker measures.* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Lastly, Figure E.6 recreates Figure 7 adding series where the average product of labor is measured using the wage bill or effective labor in the denominator. The results are qualitatively unchanged: the dispersion of average revenue products exhibits a sharp downward trend following the SAIL decision in 2001, driven mostly by large establishments.[63]

Figure E.6: SAIL and the Dispersion of Average Revenue Products of Labor and Electricity:



Note: Figure replicates Figure 7, including a series measuring the average product of labor using the wage bill and effective labor in the denominator.

E.4 Correlates of Staffing Establishment Location Choices

Our empirical analysis uses proximity to districts with more employment in staffing plants in 1990 as a shifter in the supply of staffing workers available to large, formal manufacturing plants during the 2000s. We argue this is valid both because it eased the cost of access in later years (since

[63]The result of panel b, that this is driven largely by large firms, hold with either alternative measure. Since the figure becomes messy, we omit it to economize on space.

the industry diffused spatially from these initial centers) and because the initial location decisions of staffing plants in 1990 was unrelated to demand from formal manufacturing plants. We now provide evidence of what districts with greater access to staffing plants looked like in 1990, and the characteristics of districts where staffing grew over the following 20 years.

Table E.8 regresses our measure of a district's access to staffing companies in 1990 on other district characteristics in 1990. If initial staffing access in 1990 was driven by demand from formal manufacturing plants, one would expect these districts to have greater manufacturing employment, larger manufacturing plants, a higher value-added per worker amongst large plants, and so on. However, the table suggests this is not the case. While districts with greater access to staffing plants in 1990 did tend to have greater overall employment and larger average formal manufacturing plants, the right tail of the formal manufacturing plant size distribution was thinner (row 3), plants had a lower VA / worker (either overall, row 7, or in large plants relative to small ones, row 8), and the districts were surrounded by service rather than manufacturing employment (last two rows).[64] Overall this suggests that the initial location of staffing plants in 1990 was driven more by the service-side of the local economy rather than underlying latent demand from large, formal manufacturing plants. Nevertheless, we include these seven district characteristics significantly associated with the 1990 staffing measure as district-level controls in our main analyses.

Table E.9 then relates a district's growth of employment in staffing plants in four rounds of the economic census between 1990 to 1998, 1998 to 2005 and 2005 to 2013 to manufacturing and service employment in small and large plants in the initial year (with size defined by a 100 worker cutoff).[65] Between 1990 and 1998, the growth of employment in staffing plants was unrelated to manufacturing, and driven entirely by the amount of employment in service sector plants with less than 100 workers. This changes in the second period between 1998 and 2005, where the staffing sector grew in districts with greater employment in large manufacturing plants with more than 100 workers. This pattern switches back between 2005 and 2013 where districts with greater employment in large service plants as of 2005 experienced the largest growth in staffing. These results corroborates the picture from Table E.8 that the location of the staffing sector prior to SAIL was unrelated to demand-side factors from large manufacturing plants. They also suggest SAIL may have unlocked demand for staffing from large manufacturing plants that drove the growth of the industry between 1998 and 2005, although the timing of the economic census waves prevents us from establishing this precisely.

[64] When comparing districts with any staffing plants in 1990 with those without in column 2, we see the former have more total employment but that is about it. The only other correlate which is significant is the differential VA / worker between large and small, although the magnitude is economically small.

[65] The third economic census in 1990 is the first where district-level microdata is available.

Table E.8: District Correlates with Staffing Measure

	Log Staffing	Positive Staffing
Log District Employment	0.088*	0.123***
	(0.051)	(0.030)
Log Avg Plant Size	0.191*	0.033
	(0.103)	(0.059)
P90 of Log Plant Size	-0.151**	-0.015
	(0.062)	(0.038)
Manuf Emp Share	-0.881	0.150
	(0.834)	(0.538)
Manuf Formal Emp Share	0.725	-0.162
	(0.623)	(0.387)
Share Young Plants	-0.201	-0.014
	(0.222)	(0.134)
Avg Log VA/Worker	-0.065*	0.003
	(0.039)	(0.025)
Size Diff Log VA/Worker	-0.055**	0.024*
	(0.023)	(0.014)
Size Diff Log FT Wage	-0.063	-0.013
	(0.080)	(0.044)
Log Service	2.519***	-0.087
	(0.326)	(0.143)
Log Manufacturing	-0.888***	0.082
	(0.258)	(0.117)

Note: Table reports coefficients from regressions of staffing measures at the district level on district characteristics. All variables correspond to levels in 1990. Column (1) uses the weighted staffing measure from our baseline specification. In column (2) staffing measure is a dummy for whether the district has any staffing employment in 1990. All independent variables are included. In row (1), the independent variable is log district total employment in 1990 from the economic census. Row (2) uses log average formal manufacturing plant size from the ASI. Row (3) is the 90th percentile of log formal manufacturing plant employment from the ASI. Row (4) reports results for the manufacturing share of all employment in the district, while row (5) uses the manufacturing share of all formal employment (defined as plants with more than 10 workers). In row (6) the outcome is the share of all formal manufacturing plants in the district younger than 5. Row (7) is the average of log VA/Worker amongst formal manufacturing plants. Row (8) and (9) report results for the difference in log VA/Worker and log Wage between plants with more or less than 50 workers amongst formal manufacturing plants. Row (10) and (11) refer to the weighted service measure and weighted manufacturing measure, respectively, calculated in an analogous fashion to the weighted staffing measure from the baseline specification. Sample includes 358 districts with non-missing observations. Robust standard errors reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table E.9: District Correlates with Staffing Entry

	Staffing Growth Between		
	1990 to 1998	1998 to 2005	2005 to 2013
Mfg Emp >100	-0.021	0.146***	-0.031
	(0.021)	(0.032)	(0.044)
Mfg Emp<100	0.138	0.154	-0.197
	(0.096)	(0.105)	(0.197)
Service Emp >100	-0.047	-0.065	0.146*
	(0.032)	(0.039)	(0.075)
Service Emp <100	0.387***	0.203	0.175
	(0.143)	(0.167)	(0.293)
R^2	0.09	0.16	0.01
N Obs	444	444	444

Note: Data is at the district level. Each column regresses the growth in staffing employment in a district between two years, measured as the change in the inverse hyperbolic sine of staffing employment, against district characteristics in the initial year. District characteristics are the inverse hyperbolic sine of employment in plants with more or less than 100 workers in manufacturing and service sectors. Data comes from the economic census. Robust standard errors reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

E.5 Contract Labor and the Volatility of Establishment's Product Portfolios

In an extension to the analysis in Table 5, we examine whether plants change the riskiness of their product portfolios when hiring contract labor. We might expect to see such a change given the ease with which these workers can be retrenched. Our measure of product-level sales volatility is the gross sales creation rate of each product; the idea is to capture how much sales are moving in a product category over and above the net increase in total industry sales .

To compute this measure, we consider two periods t and $t+1$. Let j index products and e index plants. For each product, we define the ratio of total sales at $t+1$ to those as t as γ_j and define adjusted sales at $t+1$ as $\tilde{Y}_{ejt+1} \equiv Y_{ejt+1}/\gamma_j$. The adjustment by γ_j implies that total adjusted sales at $t+1$ equals that at t . Therefore, net sales creation with the adjusted numbers is zero, and that gross sales creation equals gross sales destruction (allowing us to focus on gross sales creation only as our measure of volatility). The gross sales creation rate—our volatility measure—is then

$$\text{Vol}_j = \frac{\sum_{e:\tilde{Y}_{ejt+1}>Y_{ejt}>0}(\tilde{Y}_{ejt+1} - Y_{ejt}) + \sum_{e:\tilde{Y}_{ejt+1}>0, Y_{ejt}=0} \tilde{Y}_{ejt+1}}{\sum_e \tilde{Y}_{ejt+1}}.$$

The two terms in the numerator reflect growth in sales from incumbents and entrants to a product respectively, while the denominator normalizes by the average of total sales in t and $t+1$ (since this is simply adjusted sales at $t+1$). We construct two different versions of this product-level volatility measure using data from before the SAIL judgment. The first considers sales growth between 1996 and 2001, while the second considers sales growth between each pair of consecutive years between 1996 and 2001 and takes an average of these annual measures. Lastly, we compute the plant-level measure of volatility of its product portfolio by taking a weighted average of these product-level measures, where the weights are each plant's share of sales in each product code.

The results are shown in Table E.10. We find no economically meaningful differences along this margin, either in whether plants that ever hire contractors tend to produce riskier products before they adopt contract labor (odd columns) or whether plants tend to make riskier products after they start hiring contract workers (even columns). These results suggest that while plants do become slightly more likely to add new products after they adopt contractors, these new products do not tend to be any more or less risky than the products they made before.

Table E.10: Contract Labor and the Volatility of Establishment's Product Portfolios

	Ever Contract	Contract	Ever Contract	Contract
log Product Volatility, 96-01	-0.007*	-0.001	-0.004	-0.000
	(0.004)	(0.001)	(0.004)	(0.001)
log Product Volatility, Average 96-01	-0.010***	0.000	-0.006**	-0.001
	(0.002)	(0.001)	(0.002)	(0.001)
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
Establishment FE		X		X

Note: Table has the same structure as Table 5. The outcomes are volatility measures of each plant's product portfolio that capture the size of gross changes in sales within a product category relative to average total sales. The first outcome is the plant-level volatility measure constructed as defined in the text, computed using a long-difference between 1996 and 2001 to compute sales growth. The second outcome is the same measure, but defining product-volatility as the average of the annual volatility measure between each pair of consecutive years between 1996 and 2001. Standard errors clustered at the industry-level.* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

E.6 Event Studies

We complement the analysis in Table 5 with event studies that allow us to visualize changes in key plant outcomes around the first hiring of contract labor.

Sample Construction. We start off with a full sample of plants in our main dataset from 1993-2015 which we observe more than once (due to the inclusion of plant fixed effects) with non-missing values for the outcome variables. For employment as the outcome, this constitutes 815,813 observations across 172,969 plants. 75,075 of these plants hire contract labor at least once, the remaining 97,894 never hire any contractors. All of these observations are included in the regressions, but the event dummies only turn on for establishment-years in our "event sample". We define this event sample by considering a balanced panel of the 75,075 plants that ever hire contractors 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. This leaves us with 337 plants for which the event studies turn on for. This vast reduction comes primarily from the gaps in sampling in the ASI - for the 172,969 plants in this regression sample, only 16.7% are observed contiguously. Imposing plants are observed for 11 contiguous years around first hiring contractors reduces the sample a lot, but provides a balanced sample with a 5-year long pre-period to consider in the event studies.

We then run the following event study specification:

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

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 establishment 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} x years before or after first hiring contract labor. When classifying which plants the dummies is turned on for, we consider a balanced panel of plants 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.

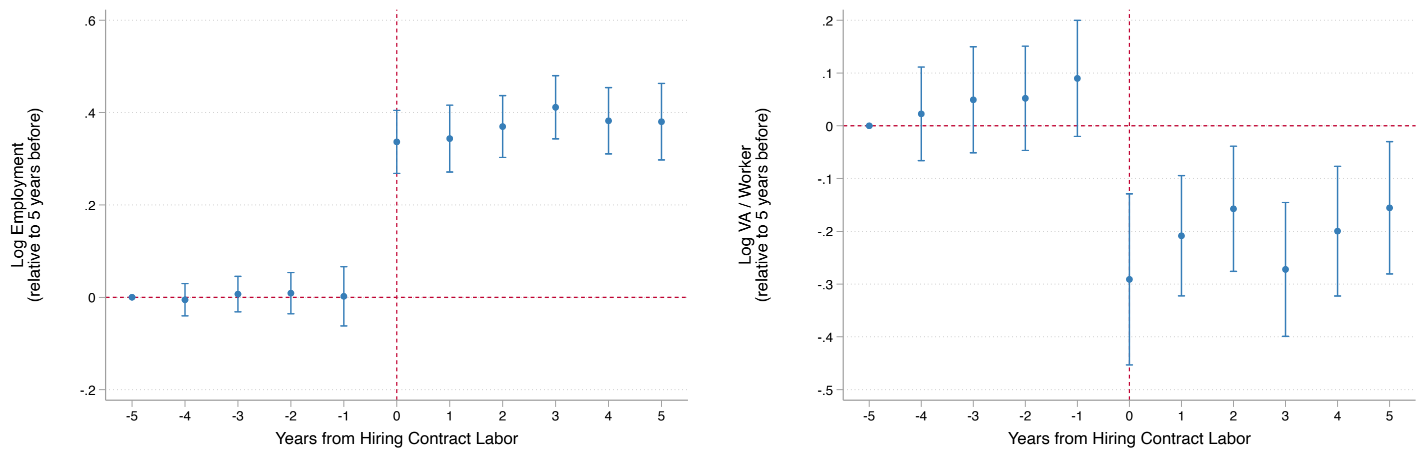
The results are presented in Figure E.7. There is a sharp rise in employment (panel (a)), as well as a sharp drop in value-added per worker (panel (b)) immediately following the hiring of contract labor. Although these event studies do not establish causality, there is no clear evidence of pre-trends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

Alternative Samples. One concern is whether these results are representative of the path of average changes in plants which hire contract labor, given the small size of this event study sample.[66] In Figure E.8, we relax the restrict to a 3- rather than 5-year contiguous window around the first year of hiring. This leaves 1,011 plants for whom the event dummies turn on, versus 337 plants in the original sample, and the new plants that come into the sample are smaller. Comparing the event studies using either criteria to define the event dummies, we see that the point estimates are statistically indistinguishable from each other.

[66] Indeed, plants in the 5-year sample are around 200% larger than other plants. This reflects the fact that large plants are more likely to be surveyed each year in the ASI by appearing in their "census" sample, and so are more likely to be observed for a long contiguous window. Plants in the 3-year sample are slightly smaller, at 174% the size of other plants. Plants that hire contract workers are much larger than those which don’t regardless of sampling criteria, as shown in the first row of Table 5.

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

(a) Employment (b) VA/Worker



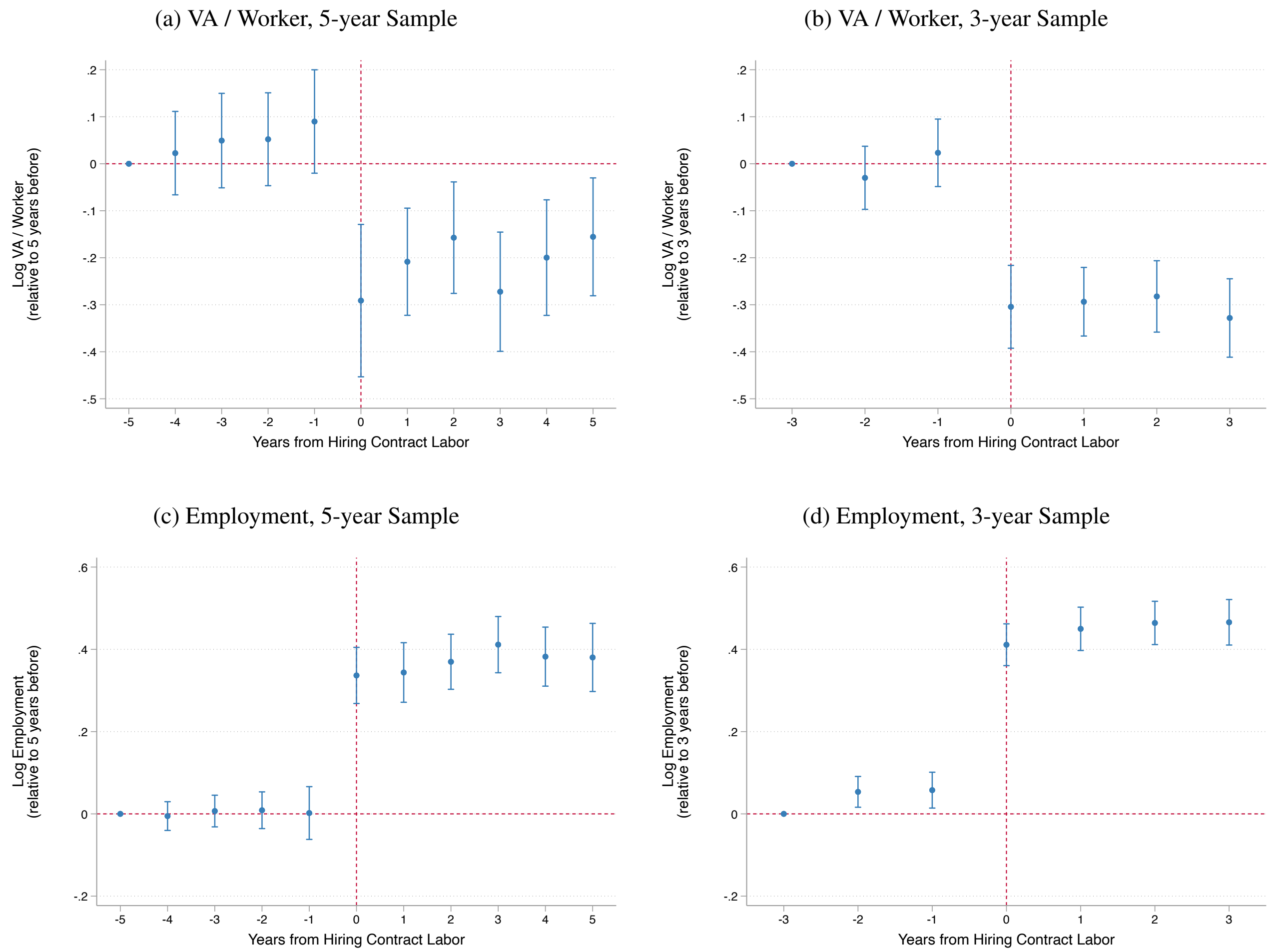
Note: Plots report coefficients and 95% confidence intervals on year from hiring contract labor dummies on each outcome, as well and industry-year and state-year fixed effects and a 4th order polynomial in plant age. Full sample is included, but year from hiring dummies only vary for plants in our sample 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. Standard errors clustered by plant.

Additional Outcomes. Figure E.9 provides evidence on how additional outcomes, sales and electricity usage, vary around the date plants first hire contractors using the same event study specification. Relative to 5 years prior to first hiring contract labor, electricity use is around 20% higher and sales 15% higher after plants begin using contractors. These are on the same order of magnitude of the point estimates for employment in the main event studies, both giving additional credance to the believability of the point estimates and showing that other measures of real activity in the plants are changing at the time that contractors are hired. Interestingly, there seem to be more pre-trends in these outcomes than for employment, suggesting that contract labor may be enabling these plants to expand its workforce in response to a rise in sales growth.

E.7 Heterogeneity in Adoption of Contract Labor Across Industries

In this subsection, we examine other drivers that could be behind the adoption of contract labor using industry-level variation in the ASI. In Table E.11 we regress either the contract labor share in each industry before SAIL (column 1) or the change its contract labor share between the pre- and post-SAIL periods (column 2) on a number of industry characteristics. First, we include an industry's standard deviation of sales since contractors may be more attractive to plants in more volatile industries. Second, we compute the fraction of workers with more than a 10th grade education in 1999 in the micro-data of the National Sample Survey in case hiring contractors is more appealing in industries

Figure E.8: Event Studies: 5-year and 3-year Samples



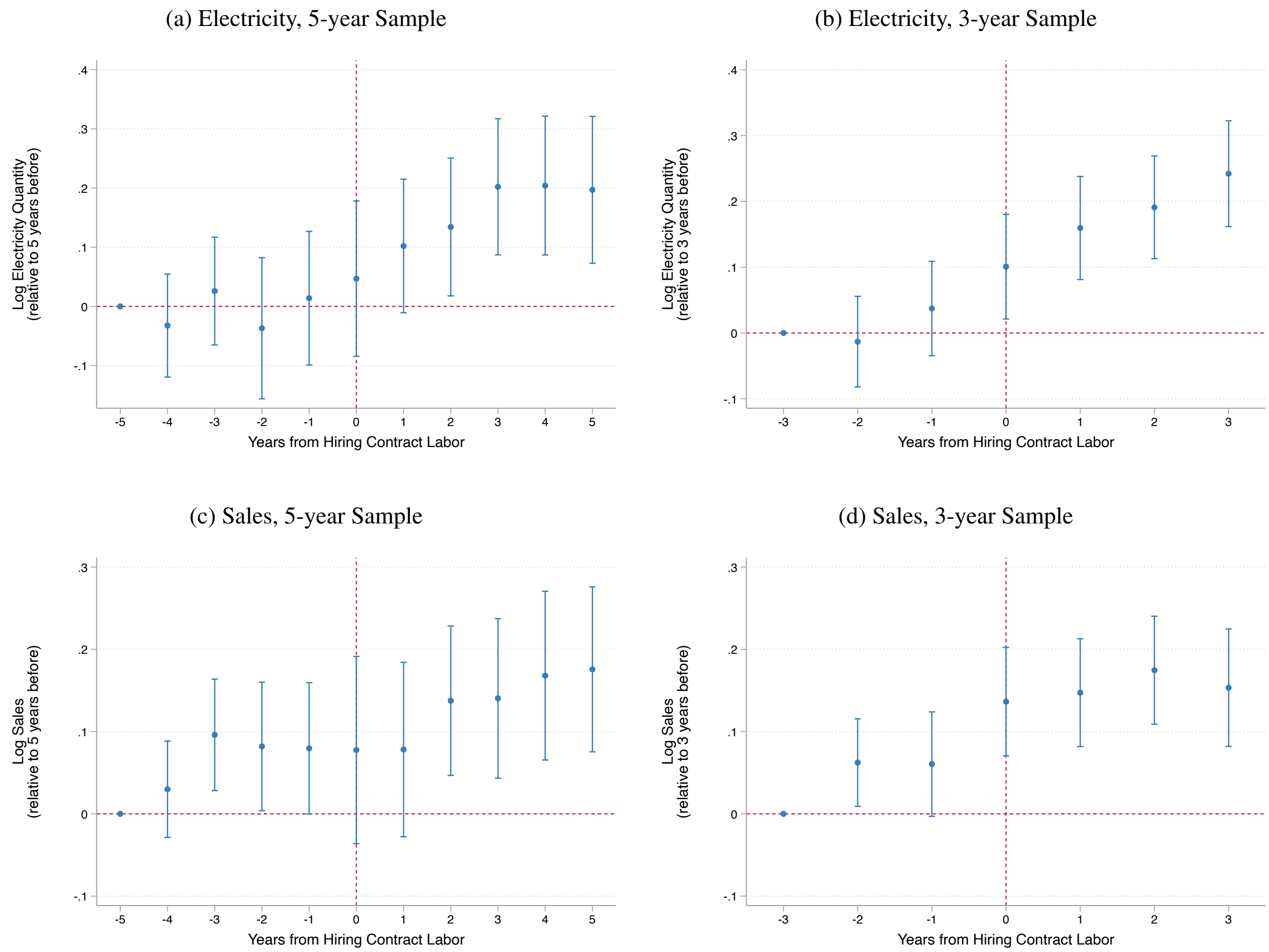
Note: 5-year sample repeats the baseline results from the paper, where there are 337 plants for which the event dummies are non-zero. The 3-year sample corresponds to the sample criteria where we allow the event studies to turn on for 1,011 plants which we observe for a contiguous 7-year period 3 years before and 3 years after the first date they hire contractors, and who hire contractors each year after the first hire. Standard errors are clustered at the plant-level.

that rely on less-educated workers.[67] Third, we measure an industry's labor share since reducing labor costs may be more attractive in labor-intensive industries. Fourth and fifth, we compute the average value-added per worker and wage bill in each industry. Seventh, we measure whether an industry was delicensed in case this drove demand for expanding through contract labor (although this period occurred in the late 1980s and early 1990s, prior to the SAIL judgment). Eighth, we measure the concentration of sales in each industry to measure whether contractors were more likely to be adopted by plants with less output market competition.

The results show very little relationship between these industry characteristics and the adoption of contract labor. No characteristic is associated with higher contract labor penetration prior to SAIL

[67] We use the NSS to calculate this number for manufacturing industries because the ASI does not have information on worker demographics and the CPHS is only available after 2017.

Figure E.9: Event Studies: Sales and Electricity



Note: Outcomes are log electricity and log sales. Specifications are the same as Figure E.8.

or higher contract labor growth after SAIL. The overall picture painted by these results is one in which contract labor was broadly adopted across industries and occupations during the 2000s, with no single type of job or industry characteristic driving these patterns.

Table E.11: Industry Correlates of Contract Labor Share

	CL Share in 1998-00	Δ CL Share 1998-00 to 2013-15
SD of Sales	0.162	-0.106
	(0.192)	(0.196)
10th Grade Pass	-0.042	0.051
	(0.071)	(0.073)
Labor Share	0.017	0.035
	(0.153)	(0.129)
Log VA/Worker	0.050	0.035
	(0.041)	(0.037)
Log Wages	0.009	-0.030
	(0.044)	(0.039)
Delicensed Ever	0.013	-0.053
	(0.046)	(0.036)
HHI	0.022	0.085
	(0.211)	(0.120)

Note: Each entry is the coefficient from industry-level regressions of the average contract labor share between 1998-2000 (column 1) and the absolute difference in the contract labor share between 1998-2000 and 2013-2015 (column 2) on the independent variable shown in the row. SD of Sales (row 1) is the standard deviation of sales growth at the establishment level: It is calculated between 1995 and 2000, where for each consecutive year the difference in log sales is calculated for the panel of plants; the standard deviation is calculated each pair of years after which a grand mean is taken. 10th grade pass (row 2) is the share of formal workers in the industry in the NSS data who have passed 10th grade education. Labor share (row 3) is the share of total wages in value added, log VA/Worker (row 4) is the log of the ratio of value-added to total employment, and log wage bill (row 5) is the log of total wages, all calculated over 1998 and 2000. Delicensed Ever (row 6) is a dummy for whether the industry is delicensed in either year 1985 or 1991 based on Aghion (2008). HHI (row 8) is the Herfindahl of the industry, averaged across 1999 and 2001. Robust standard errors are reported in parentheses. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

E.8 Wage Gap between Permanent and Contract Workers

We use the CPHS data to estimate the wage gap between permanent and contract workers after controlling for worker characteristics. Specifically, we run Mincer-style regressions that measure relative wages for permanent and temporary workers holding constant worker observables, shown below in Table E.12. We find, at least in the more recent period when this data is available, that contract workers earn about 25% less than observationally similar permanent workers in their industry in terms of age, gender, and education. The coefficients are stable as we add in gender, gender-by-age and educational fixed effects. We note that the 25% gap lines up with the gap from the ASI as measured in Figure 9.

Table E.12: Earnings Difference Between Permanent and Contract Workers in Formal Manufacturing

	(1)	(2)	(3)	(4)	(5)
Contract Worker	-0.252**	-0.251***	-0.250***	-0.235**	-0.231***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
State FEs	X	X	X	X	X
Industry FEs	X	X	X	X	X
Quadratic in Age	X	X	X	X	X
Gender		X	X	X	X
Gender-Age FEs			X	X	X
Education FEs				X	X
Caste FEs					X

Note: Table shows coefficient from regression of log(earnings) on a contract worker dummy. The sample includes contract and permanent workers employed in non-managerial occupations in the formal manufacturing sector. Data for this regression comes from the CPHS May - Aug 2017 wave. All specifications include state and industry fixed effects as well as age and age-squared as controls; (2) further includes a dummy for whether the person is female; (3) further includes controls of interactions between the female dummy and age and age-squared; (4) further includes dummies for the person's educational status; (5) further includes indicator variables for caste groups (intermediate caste, not stated, other backward castes, scheduled caste, scheduled tribe, and upper caste). Each observation is weighted using CPHS's weight for population aged 15 or higher. Robust standard errors reported. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

E.9 Permanent Workers' Characteristics and Contract Labor Share

We assess whether the patterns in Figure 11 could be explained by increased negative selection of permanent workers when the contract labor share increases. In particular, Table E.13 uses the CPHS data and shows regressions of the change in the characteristics of permanent workers in an industry on the change in the share of contract labor in that industry, where both are measured between 2017 and 2022 (the period for which the CPHS is available). We fail to find evidence of negative selection among the remaining permanent pool as the contract labor share increases. If anything, the selection looks positive, with permanent workers being somewhat older and slightly more educated as the contract labor share in their industry increases. This suggests the patterns in Figure 11 may be understating the reduction in costs for permanent labor.

Table E.13: Contract Labor Share and Permanent Formal Manufacturing Workers' Characteristics

	Age	10th Grade Pass	12th Grade Pass	Female	Upper Caste	Scheduled Caste	Hindu
Contract Labor Share	2.098*** (0.651)	0.039* (0.021)	0.079** (0.033)	0.027 (0.017)	-0.018 (0.024)	-0.031 (0.027)	0.012 (0.015)
R^2	0.30	0.39	0.41	0.14	0.54	0.39	0.70

Note: Data is at the wave-state-industry level. Wave refers to a wave of 4-months over which the CPHS surveys are conducted. Data covers May 2017 to Aug 2022. Only temporary and permanent workers in the formal manufacturing sectors are included. Table reports coefficients from regressions of mean characteristics of permanent workers at the wave-state-industry cell on the average contract labor share in that cell. Contract labor share is calculated as contract workers divided by the sum of contract and permanent workers. Industries are CMIE industries. Industry, state, and wave fixed effects are included. CMIE's weights for population aged 15 or higher are applied before collapsing the data to the wave-state-industry level. Robust standard errors reported in parentheses. Number of observations = 2,515.* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

E.10 Testing for Break in VA / Worker Trend Around SAIL

Figures 5 and E.5 provide evidence of a break in trend in the elasticity of value added per worker to plant size after SAIL. However, this effect is noisy due to the size of confidence intervals when standard errors are clustered by industry. Table E.14 tests whether the break in trend is significant around SAIL. It regresses log value added per worker on a full interaction of log plant size, a linear time trend t, and a post-SAIL dummy. The coefficient on the triple interacton measures $\mathbb{E}[\partial^2 \ln(VA/Worker)/\partial \ln(Emp)\partial t|\text{Post-SAIL}] - \mathbb{E}[\partial^2 \ln(VA/Worker)/\partial \ln(Emp)\partial t|\text{Pre-SAIL}]$, i.e. the difference in the slope of the elasticity with time before and after SAIL. It does so measuring labor using the number of workers as in the paper, or using the wage bill or effective units of labor as in appendix. We see that in all cases the difference is significant, although not always extremely precise. This is perhaps predictable given the confidence intervals in the figures.

Table E.14: VA / Worker - Size Elasticity: Time Trend Triple Diff Pre- and Post-SAIL

	log VA / Worker	log VA / Wage Bill	log VA / Effective Worker
log L X t X PostSAIL	-0.007*		
	(0.004)		
log wL X t X PostSAIL		-0.004**	
		(0.002)	
log Effective L X t X PostSAIL			-0.010***
			(0.003)
R^2	0.42	0.27	0.24
N	971,494	931,754	515,456
Full Interaction	X	X	X
Industry X Year FE	X	X	X

Note: Table reports results from a regression of outcome of the full interaction between logL (column 1), log Wage Bill (column 2) or log Effective Labor (column 3) and a linear time trend and a Post Sail dummy (i.e. a triple difference regression). Table reports only the coefficient on the triple interaction term, which reports the difference in the trend in the elasticity in the post vs pre SAIL periods. Standard errors clustered by industry.* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

E.11 Supporting Materials for Section 8

Table E.15: Earnings Differences by Employment Arrangement: Manufacturing Sector

	<10 Years	10-12 Years	>12 Years
Permanent-Formal	0.439***	0.565***	0.729***
	(0.036)	(0.032)	(0.048)
Permanent-Informal	0.233***	0.238***	0.460***
	(0.021)	(0.024)	(0.046)
Contract-Formal	0.255***	0.311***	0.494***
	(0.027)	(0.028)	(0.053)
Contract-Informal	0.126***	0.183***	0.388***
	(0.020)	(0.025)	(0.047)
Self-Employed	0.189***	0.335***	0.777***
	(0.031)	(0.032)	(0.051)
R^2	0.40	0.41	0.44
N	7,622	7,312	4,705
State FEs	X	X	X
Industry FEs	X	X	X
Age, Age Squared	X	X	X
Gender	X	X	X
Gender-Age FEs	X	X	X

Note: Table regresses log(earnings) across workers employed in manufacturing based on their employment arrangement. The missing category is daily wage/casual employment. All regressions include a quadratic in age, a gender dummy, interaction of the gender dummy with the quadratic in age, and fixed effects for state and industry (as measured in the CPHS). Separate regressions are estimated for individuals with less than 10 years of schooling, between 10 and 12 years of schooling, and more than 12 years of schooling. Earnings include business profits for self-employed workers. "Formal" is defined based on whether or not a given worker has access to a provident fund; see Appendix C for details. Data for this regression uses the CPHS May - Aug 2017 wave. Each observation is weighted using CPHS's weight for population aged 15 or higher. Robust standard errors reported. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table E.16: Distribution of Employment Arrangements in Manufacturing by Educational Attainment

Employment Arrangement	Years of Schooling: <10	>12	10 to 12	All
Daily Wage/ Casual labor	0.37	0.04	0.16	0.23
Permanent-Formal	0.07	0.27	0.17	0.14
Permanent-Informal	0.11	0.20	0.16	0.14
Contract-Formal	0.04	0.11	0.10	0.08
Contract-Informal	0.27	0.22	0.27	0.26
Self-Employed	0.13	0.16	0.14	0.14

Note: Table reports the distribution of manufacturing workers across employment arrangement categories. Results are reported overall, as well as by education groups: less than 10 years of schooling, between 10 and 12 years of schooling, and more than 12 years of schooling. "Formal" is defined based on whether or not a given worker has access to a provident fund; see Appendix C for details. The sample covers CPHS data from May 2017 to Apr 2018. Each observation is weighted using CPHS's weight for population aged 15 or higher.

Table E.17: Transition Rates Between Employment Arrangement

Employment Arrangement in t	Employment Arrangement in t+1: Daily Wage	Not Employed	Permanent	Contract Informal	Contract Formal	Self-Employed
Daily Wage	0.555	0.132	0.020	0.049	0.002	0.242
Not Employed	0.026	0.921	0.007	0.012	0.001	0.034
Permanent	0.048	0.107	0.561	0.086	0.029	0.168
Contract-Informal	0.147	0.143	0.115	0.347	0.031	0.217
Contract-Formal	0.047	0.100	0.322	0.074	0.302	0.153
Self-Employed	0.129	0.099	0.039	0.035	0.003	0.694

Note: Table calculates transition rates between employment arrangement over a year in 3 waves of the CPHS data (May - Aug 17, Sep - Dec 17, Jan - Apr 18) and takes the average transition rate across the three waves. Sample includes all adults (men and women), in all sectors (including those not-employed). "Formal" is defined based on whether or not a given worker has access to a provident fund; see Appendix C for details. Permanent includes formal and informal workers.

F Theory Appendix

F.1 Value Function Derivation

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

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

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

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

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

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

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

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

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

F.2 Value Function Simplification

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

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

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:

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

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

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

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

For high-type plants, the solution is

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

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

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

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 $k \in \{L, H\}$.

F.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 step sizes and we consider a BGP so that the distribution of relative productivity 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 $E[\hat{q}] = \int_0^\infty [1 - F(\hat{q})]\, d\hat{q}$. Inverting the order of integrals, the integral on the right becomes $\int_1^\infty \int_0^\infty [1 - F(\hat{q}/\lambda)]\, d\hat{q} dG(\lambda)$. Using the change of variables $x = \hat{q}/\lambda$ so that $d\hat{q} = \lambda dx$ we get

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

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

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

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

Finally, to define the share of products owned by high-type plants ϕ, we use similar manipulations to define the productivity distributions of products owned by low- and high-type plants 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 $F(\hat{q}), F_L(\hat{q}), F_H(\hat{q})$

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

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

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

The share of products owned by high type plants is then

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

F.4 Static Allocations

The solution to the hiring problem is

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

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

Labor market clearing then implies

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

where we normalize the price index to one.[68] Replacing this into the expression for labor delivers $\ell_j = \hat{q}_j^{\sigma-1}\left(1+[1-\mathbb{I}_j]\,x\kappa_k\right)^{-\sigma}L$, where we define $Q = Y/L$ and $\hat{q}_j = q_j/Q$. Prices and sales are therefore $p_j = \left(1+[1-\mathbb{I}_j]\,x\kappa_k\right)Q$ and $p_j y_j = \hat{q}_j^{\sigma-1}\left(1+[1-\mathbb{I}_j]\,x\kappa_k\right)^{1-\sigma}Y$, while profits are given by

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

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

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

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

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

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

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

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

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

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

F.5 Alternative Production Functions

In this appendix, we consider alternative production functions.

First, suppose that a firm adds layers of hierarchy depending on the quality of its products. Specifically, output of a variety is given by $y_j = M_j^\gamma \, l_j$, where M_j denotes the number of management hierarchies and $\gamma < \frac{1}{\sigma-1}$ is the elasticity of output with respect to M_j. The rest of the model is the same. First, holding M_j fixed, it is easy to show that revenues, profits, and employment are proportional to $\left(\frac{q_j \, M_j^\gamma}{1+\mathbb{I}_j x\kappa}\right)^{\sigma-1}$.

Next, suppose that the marginal cost of a marginal increase in the number of management hierarchies M_j is constant (and same for all products). After equating the marginal increase in profits from an increase in M_j with the marginal cost of M_j, the optimal number of hierarchies M_j is proportional to $\left(\frac{q_j}{1+\mathbb{I}_j x\kappa}\right)^{\frac{\gamma}{1-\gamma(\sigma-1)}}$. Remember $0 < \gamma(\sigma-1) < 1$ so the IDA, as parameterized by $x\kappa$, lowers the number of management hierarchies, ceteris paribus. Intuitively, the IDA makes firms reluctant to invest in management hierarchies. In addition, the effect of an increase in q_j on revenues, employment, and profits is larger in this model with endogenous management hierarchies.

Substituting the expression for M_j into the expressions for revenues, profits, and employment, we get that these three endogenous objects are proportional to $\left(\frac{q_j}{1+\mathbb{I}_j x\kappa}\right)^{(\sigma-1)\,\frac{1+\gamma(\sigma-1)}{1-\gamma(\sigma-1)}}$, and aggregate output is $Q = \left(\int_0^1 \left(\frac{q_j}{1+[1-\mathbb{I}_j]x\kappa_k}\right)^{(\sigma-1)\,\frac{1+\gamma(\sigma-1)}{1-\gamma(\sigma-1)}} dj\right)^{\frac{1}{\sigma-1}}$. Intuitively when M_j is endogenous, the IDA has a larger effect on the allocation of labor, and thus the static losses from the misallocation of labor are also correspondingly larger. Similarly, improvements in product quality q_j also have a larger *positive* effect on aggregate output when M_j is endogenous.

However, it should be clear that endogenous management hierarchies is akin to multiplier that amplifies the effect of innovation (and misallocation). In the absence of improvements of product quality (or changes in the distortion faced by the high-type firms), the creation of management hierarchies affects the level of output but has no effect on long run growth or job creation.

The last result for this alternative production function is that the marginal product of labor of products of high-type firms that use full time workers is still given by $\left(\frac{\sigma}{\sigma-1}\right) w\left(1 + x\kappa\right)$, and the marginal product of labor of products of low type firms and products of high-type firms that employ contract labor is given by $\left(\frac{\sigma}{\sigma-1}\right) w$ even when M_j is endogenous. Intuitively, endogenizing M_j implies that the IDA has a larger effect on revenues *and* on employment, and the ratio of the two is unchanged compared to the model where M_j is exogenous.

As a second alternative model of the production function, suppose that the two types of workers are imperfect substitutes, even after adjusting for quality. Specifically, suppose output of a variety of a high type plant that pays the fixed cost to hire contract labor is given by $y_j = \left(\ell_{Fj}^{\frac{\rho-1}{\rho}} + \ell_{Cj}^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho}{\rho-1}}$ where ℓ_F and ℓ_C denote permanent and contract workers and ρ is the elasticity of substitution between these two types of workers. When the two types of workers are imperfect substitutes, a given change in the fixed cost of using contract labor has a smaller aggregate effect. However, since the change in the fixed cost has to match the change in contract labor use observed in the data, a smaller value of ρ implies that the change in fixed cost has to be much larger to "explain" the same increase in the use of contract labor. These two effects of imperfect substitution – a larger decline in the fixed cost and a smaller effect of a given change in the fixed cost – offset so the aggregate effect is invariant to ρ.

G Estimation and Quantification: Simulation Algorithm

G.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 plants, each of which holds one product.
4. Simulate life paths for the plants. Specifically, each period, both incumbent and entering plants innovate upon products, as specified in Section **??**. Products change hands accordingly, and some plants 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 establishment. Hiring decision by plants 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.[69]
7. Once the model attains stationarity, we compute the targeted moments (specified in Table 8) 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 7.1 and 7.1.

G.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.

[69] 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 plants, each of which holds one product.

4. Simulate life paths for the plants. Specifically, each period, both incumbent and entering plants innovate upon products, as specified in **??**. Products change hands accordingly, and some plants 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 7.1 and 7.1.

5. In addition, in each period, compute employment at each establishment. Hiring decision by plants 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.[70]

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

8. Repeat 1-7 searching for F to exactly match the targeted moment (percentage of large plants 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.

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