No Country for Dying Firms: Evidence from India[*]

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Abstract

Why is India a laggard when it comes to manufacturing, especially the labor-intensive kind, while doing much better in the technology sector? We classify states into good and bad states according to their size-adjusted entry rates in manufacturing on the grounds that states with high entry rates must be attractive to firms. We argue that Indian institutions create frictions to firm exit and adjustment, especially in labor-intensive manufacturing. We document this by showing that the data patterns and the way manufacturing firms in good versus bad states respond to these frictions is as predicted by theory. We then develop and estimate a dynamic heterogeneous firm model with entry, exit and input (labor and capital) adjustment costs. Our estimates are sensible and our counterfactual exercises show that exit costs play a critical role in explaining India's lackadaisical performance in manufacturing production and exports.

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1 Introduction

Schumpeterian creative destruction, whereby new and better production units push out outdated ones, drives the economy to its technology frontier. Structural impediments to this process can become a major drag on productivity growth and economic development. In particular, frictions to exit, like bankruptcy costs and factor adjustment costs, result in lower entry and a less dynamic economy. In this paper, we use micro-data from India on manufacturing plants to study the importance of exit costs on India's development.

Studying the aggregate impact of exit barriers is important for policy-making and from the point of view of development economics. It has been tempting for policymakers across the world to put restrictions on firing workers and/or the exit of firms as a way to maintain employment and output, but the actual outcome is quite the opposite. Impediments to exit can take the form of labor regulations (such as in India and France), require contributions to unemployment insurance (as in the U.S.), or make bankruptcy proceedings time-consuming and costly (Djankov, Hart, McLiesh, & Shleifer, 2008). Once firms realize that these regulations reduce their expected profits, they choose not to enter, to begin with. In addition, resources are misallocated as low-productivity firms do not exit, thereby tying up resources that could be better used elsewhere. The lower entry and productivity result in lower labor demand and hence, lower wages as well. Thus, total employment is lower in equilibrium, defeating the (often explicitly stated) purpose of such regulations in addition to reducing output and productivity.

We choose our empirical context to be India's manufacturing sector for two reasons. First, India is now the world's largest country, but several puzzles related to India's macro-development and structural transformation do not have a coherent explanation. These include India's pre-mature deindustrialization (Rodrik, 2016), the existence of a long tail of unproductive firms (Hsieh & Klenow, 2014), and under-performance in key low-skill manufacturing sectors (Chatterjee & Subramanian, 2023).

Second, in India, there are various institutional and non-institutional barriers to exit that

vary across states. This, along with the availability of a rich longitudinal dataset on firms that records unique information on plants after they stop production while waiting to exit, gives us the perfect laboratory to identify and estimate these costs.

Third, prima facie evidence exists that exit costs in India are high. India has one of the lowest firm exit rates in the world (see 1a below), and a large fraction of firms in India remain dormant (i.e., they are registered and may even employ workers but do not run operations/produce output) for a long time before they finally exit. 20% of all registered firms in India are dormant, and 35% of all registered firms between 1981-1990 were inactive by 2016, i.e., they were in the process of liquidation but had not exited (Sengupta & Singh, 2019). [1] It is well known that such exit delays, especially for distressed firms, cause a huge burden on banks. Firms in India mostly borrow from public sector banks, which often have to bear the firm's costs during dormancy. Such practices have contributed to India's non-performing assets (NPA) problem.[2]

Even if a firm is not embroiled in any litigation or dispute and all relevant paperwork is in place, its voluntary closure takes approximately 4.3 years. 2.8 years are spent alone on obtaining clearances and security refunds from various government departments like Income Tax, Provident Fund, Goods and Services Tax, etc. In contrast, voluntary liquidation takes about 12 months in Singapore, 12-24 months in Germany, and 15 months in the United Kingdom (Economic Survey of India 2020-21). Since the efficiency of government departments vary by state, the time taken to obtain these clearances can also vary a lot by state.

Our analysis has two parts. First, we provide evidence, both associations and causal, that exit barriers impose significant costs on firms in India, resulting in the misallocation of resources, entry deterrence, and in a long tail of very old firms with low productivity. Second, we build and estimate a firm dynamics model to quantify the effect of these frictions on India's aggregate productivity and growth. Exit barriers could be institutional and easier to model.

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[1] Numbers in the ASI data are lower; around - percent are dormant with workers, and - percent are dormant without workers. This is to be expected as firms that are dormant without workers are dropped from the data after three years.

[2] See V. Kaul (2020) for an excellent account of India's banking crisis.

For example, those coming from labor regulations or imperfect land and capital markets. But they could also be unobserved, like variations in the implementation of similar policies or idiosyncrasies in judicial outcomes across states. Our approach captures both. In particular, first, we allow for flexible functional forms to estimate labor and capital adjustment costs. Second, we incorporate unobserved fixed costs of production as well as a scrap value of firms to capture exit costs explicitly. Higher fixed costs make it more likely for a firm to stop producing but remain in the market. A higher scrap value means lower exit costs and makes a firm more likely to choose to exit.

The broad mechanism that we are proposing here is not new. For example, there is a literature on sunk costs of entry that builds on Hopenhayn (1992) and Hopenhayn and Rogerson (1993). For example, Roberts and Tybout (1997), and Das, Roberts, and Tybout (2007). Such costs, in effect, discourage exit in response to bad shocks. Our main focus here is a quantitative evaluation of this critical mechanism in an important setting where puzzles on macroeconomic development remain unexplained.

That being said, the literature has ignored the general equilibrium effects of exit costs on firm entry and the interactions between various policies that drive exit costs. Studies have largely focused on the country by country's specific regulations or frictions (like labor regulations, bankruptcy regulations, government subsidies, and land market frictions). For India, in particular, we know of no prior work like our paper.

On specific frictions, perhaps the most extensive literature is on labor regulations, employment protection, and the consequences of firing costs across a number of countries. Papers span both reduced form (Besley & Burgess, 2004; Autor, Kerr, & Kugler, 2007; Adhvaryu, Chari, & Sharma, 2013; Chaurey, 2015; Amirapu & Gechter, 2020) and structural methods (Guner, Ventura, & Xu, 2008; Cooper & Willis, 2009; Lapatinas, 2009; Poschke, 2009; Da-Rocha, Restuccia, & Tavares, 2019; Mukoyama & Osotimehin, 2019; Padmakumar, 2022; Bertrand, Hsieh, & Tsivanidis, 2021).

In India, one of the main laws regulating the firing of workers is the Industrial Dispute

Act of 1947. The literature has examined its impact by building indices based on reforms in this law which occurred differently over time in various states, see (Besley & Burgess, 2004, the foundational paper in this area. They create an index of the stance in terms of labor by looking at the amendments made by each state to the central legislation on labor regulations. They show that states in India that amend labor regulation in a pro-worker manner have lower output, employment, investment, and productivity in formal firms.

Using this index and rainfall as an instrument, Adhvaryu et al., 2013 shows that industrial employment is more sensitive to shocks where labor regulation is less restrictive. Chaurey, 2015 shows that firms in Indian states with more restrictive labor laws hire more contract workers, but not more permanent workers (who are covered by the law) in response to transitory local demand shocks.

There are three main shortcomings to this approach. First, such indices are far from perfect and have been heavily criticized (see e.g. Bhattacharjea, 2006). Second, the implementation of these laws is both imperfect and uncertain. A lot is left to the discretion of the courts and authorities, making outcomes uncertain.[3] Rulings in lower courts have been extreme and often overturned by higher courts.[4] Third, there are many non-legal reasons, like political constraints that create exit costs and which are not fully captured by the indices. Fourth, none of these papers focus on the macro implications of labor regulations. Building on Cooper and Willis (2009), our approach is able to estimate labor adjustment costs more broadly and quantify the macro implications of the same.

There is far less work on the role of exit barriers other than on labor regulations. Exceptions are the work on capital adjustment costs (e.g Cooper & Haltiwanger, 2006), government subsidies as exit barriers (Chu, 2000), and bankruptcy in finance as these costs act as exit barriers (e.g. White, 2016; Bernstein, Colonnelli, Giroud, & Iverson, 2019; Corbae &

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[3]Issues include whether the IDA covers only manufacturing, mines, and plantations as stated in the act, or not. What constitutes a workman, i.e., a regular worker, and what is the definition of a contract worker?

[4]For example, in the case of Bharat Forge Co Ltd v Uttam Manohar Nakate, the worker, Nakate, was repeatedly found sleeping on the job and dismissed. However, the lower courts forced his reinstatement with some back pay. Only after 22 years, did the supreme court finally allow his dismissal.

D'Erasmo, 2021). Easing barriers to firm liquidation has been important for the historical growth of modern industrial nations. Di Martino (2005), for example, argues that the early introduction of bankruptcy codes in England and in the United States was a factor in the more vibrant private sector in these countries. In contrast, the commercial codes in Italy and France based on the Napoleonic code were seen as discouraging firm failure and hence greatly affecting the ability of economies to adjust (Bignon & Sgard, 2007).

In India, till relatively recently as discussed in Section 2.3 below, there was no well-defined path to bankruptcy. The most recent reform was the formulation of the Insolvency and Bankruptcy Code (IBC) in 2016 which was then put on hold during COVID. However, even the IBC has had very limited success due to judicial bottlenecks and court congestion. Akcigit, Alp, and Peters (2021) argues that part of the reason might be the difficulty in enforcing contracts in India arising from an overtaxed judicial system. As a result, firms remain family run which can constrain their expansion and efficiency. Finally, frictions in land markets also contribute to exit costs and misallocation as buying and selling land for industrial purposes in India is hard, see (Sood, 2020), who focuses on frictions in acquiring land for manufacturing. Note that rather than constraining ourselves to a particular source of exit costs, we capture a plethora of measurable and un-measurable exit costs in our estimates of scrap value: a low scrap value means high exit costs.

Focusing on specific regulations may suffice for studying firm exit in advanced countries because other factors might be limited, the analysis would be incomplete for developing countries and especially India. First, in developing countries, there can be multiple factors that interact with each other that add up to a large exit cost. Second, since the interpretation and implementation of laws are imperfect, a reduced-form approach is at best incomplete and at worst incorrect. Moreover, many of the factors that stall exit may be extra-legal or unmeasurable, and thus ignored in existing analyses. Finally, the general equilibrium effects on entry and thorough the interaction of various policies regulating exit may be large. Our approach makes advances on all these fronts.

The paper proceeds as follows. In Section 2, we provide more details about the institutional context. In Section 3, we discuss data sources and challenges with measuring exit in Indian data. In Section 4, we provide some empirical patterns as well as more causal evidence regarding how firms seem to respond to exit barriers. In Section 5 we build our dynamic model that explicitly tries to capture, in a flexible way, both labor market frictions created by size based regulations as well as exit costs. In Section 6 we provide intuition on what identifies the key parameters and provide some preliminary estimates. Section 8 concludes.

2   The Institutional Context

Firms take a long time to exit in India. Even if a firm is not embroiled in any litigation or dispute and all relevant paper work is in place, its voluntary closure takes approximately 4.3 years. 2.8 years are spent alone on obtaining clearances and security refunds from various government departments like Income Tax, Provident Fund, Goods and Services Tax, etc. In contrast, voluntary liquidation takes about 12 months in Singapore, 12- 24 months in Germany and 15 months in the United Kingdom (Economic Survey of India 2020-21). Since efficiency of government departments vary by state, the time taken to obtain these clearances can also vary a lot by state.

In addition to the above, if a firm gets entangled in legal disputes then it substantially increases the time to exit (see Section 2.1 for an example). As worker retrenchment and firm liquidation are regulated by various federal and state laws, their history, intent, and interpretation by courts shape the frictions to exit. Moreover, both the laws and their interpretation by courts evolve over time, giving rise to uncertainty in judicial outcomes. We illustrate the challenges to exit first through a specific case study. Then we discuss the history and complexities in the implementation of the most important labor and bankruptcy laws in India.

2.1 The Exit of Nokia's Largest Factory: A Case Study

Nokia announced its plan to set up a plant in India on December 2004. At that point it sold about a million phones a month in India, all imported from China. Its goal was to increase this to six to seven million a month by reducing transaction and adjustment costs. Soon various state governments started to woo the company by offering them various incentive packages. In the end Tamil Nadu won because of two reasons in addition to the tax holiday. First, the Chennai International Airport was only 33km away from the proposed special economic zone in Sriperumbudur. Second, the party in power (AIADMK) in the state was in coalition with the ruling party (Congress) at the center and the national Minister of Communications and IT belonged to AIADMK. Thus, the project had the blessing of both the central and state political rulers. Production started in 2006.

Between 2006–2012 this factory became the poster child of capitalism. This was Nokia's largest operation anywhere in the world. At its peak, the factory employed close to 20,000 employees and produced 15 million phones a month which were exported to 80 countries. About 70% of these employees were women.

Troubles started in 2013. Labor held strikes and lockouts demanding better working conditions and expecting a raise. The death on the job of a female assembly operator further fuelled discontent. The success of the factory attracted political attention as they saw the employees as a vote bank. A DMK-backed (the party in opposition of AIADMK) labor union gained ground around 2010.

There was tough competition in the international market as well. As the tax holiday came to an end, the incentives provided by Vietnam made it an even more attractive production destination. Moreover, cellphone technology was rapidly changing toward smartphones. The nail in the coffin were perhaps two tax evasion cases against Nokia – one by state authorities and the other by central authorities. While the Madras High Court later set aside the demands by state authorities, Nokia's assets linked to this factory were frozen by the Supreme Court of India in October 2013 due to the latter tax case.

Meanwhile, given the churn in cellphone technology and the global market, Nokia sold its devices and services business to Microsoft for USD 7.2 billion in April 2014 but the Indian factory was excluded from the deal owing to the legal challenges it was embroiled in. Intially, Microsoft wanted to use the factory as a contract manufacturer for low-cost cellphones but soon decided against it and production came to grinding halt.

At the factory, several contract workers not protected by labor laws were laid off. However, the permanent workers couldn't be. With the asset freeze in place, Nokia could not sell the factory either so was required to pay the workers as long as the tax dispute continued. Some permanent workers took voluntary retirement and severance payments by offered by the company. Nokia did this because once the tax dispute got resolved, in order to close the factory it would need approvals from the government and an agreement with the labor unions. Lawyers say that "7 or 8 out of 10 such cases are rejected" as "welfare statutes look out for the interest of employees". They advise that getting these permissions are easier if the employee headcount is low before the firm seeks government approval.

Nokia settled the tax dispute in 2018 by paying a penalty of 202 million euros, but even 4 years after production stopped it was uncertain whether it would be able to sell its factory owing to some other litigation that arose in the interim years. Finally, in 2020, after a gap of 6 years, the Chinese firm Salcomp bought and started manufacturing cell phone chargers with 1000 workers in the factory that was once the globally most productive cellphone factory.

This example illustrates three things. First, there is a great deal of political, judicial, and institutional complexity and uncertainty related to firm exit. Second, it illustrates the gargantuan delays in the administrative processes. Third, that this happened in the state of Tamil Nadu – a pro-employer state according to the Besley-Burgess measure – suggests that it might have been even worse in pro-labor states and that the letter of the law alone cannot be used as a measure of exit costs.

2.2 Labor Laws, Hiring, and Firing Labor

The Industrial Dispute Act (IDA) of 1947 is one of the many laws regulating labor in India and has been the subject of much research in economics. In this section, we provide some clarifications regarding the IDA and labor regulations. First, the IDA is not the only law regulating labor in India. The origin of labor laws goes back to the pre-Independence British Raj. Many important laws that form the backbone of the labor law system today were formulated in the 1920s. These include the Factories Act of 1922, the Mines Act of 1922, the Workmen's Compensation Act of 1923, the Trade Union's Act of 1926, and the Trade Disputes Act of 1929.

Since labor is a topic under the concurrent list[5] of the constitution, both the central and state governments are competent authorities to enact legislation pertaining to labor. In the state of Maharashtra for example, 48 state and national laws regulate labor.[6] West Bengal has 31 acts,[7] and Telengana has 47. Overtime the IDA itself has been differentialy amended by various states creating variation in the legal environment across states and that variation has been used for research starting with the seminal work by Besley and Burgess (2004).

However, the letter of the law is an incomplete assessment of how it is actually implemented. For example, one of the most stringent provisions in the IDA is the requirement for firms to report to the government if they retrench workers and the need to obtain prior permission if firms are above a certain threshold (was 100 workers and is now 300 workers after the 2021 reforms). It is not straightforward to obtain such permission, and a lot is left to the discretion of the authorities making outcomes uncertain.

The second complication is related to judicial efficiency and outcomes. With only 1 court per 500,000 workers, courts are heavily backlogged and cases can take years to get resolved.

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[5]The Indian constitution divides legislation topics into three lists–central, state, and concurrent. International Trade for example is in the central list and only the national parliament can enact laws related to international trade (e.g. decide tariff duties). Agriculture on the other hand is a state subject. Labor, internal trade and commerce are concurrent subject allowing both the national parliament and the state legislatures to enact laws on these matters.

[6]https://mahakamgar.maharashtra.gov.in/acts-rules.htm

[7]https://wblc.gov.in/acts-rules

The number of cases pending before Labour Courts as of October 2020 was over 100,000 - 35% of these cases had been pending for over a year and out of these 37% had been pending for more than 3 years. [8] Rao (2021) has shown that there is substantial variation across states in court efficiency. Hence, costs of adjustment could vary not only because of the law but also due to the speed of dispute resolution in courts. In principle, these may go in opposite directions.

However, the biggest hurdle, however, comes from the uncertainty that firms face while making decisions, should they get dragged into a labor court. The court's interpretation of the laws has evolved. Sarkar (2019) documents that while many specific statutes did not greatly change over time, the judiciary's interpretations of them changed over the last six decades based on the dominant socio-political currents and government economic policies. As India embraced free markets, so did her courts. Furthermore, even within a short span of time, courts often give contradictory judgments across cases that prima facie appear similar. B. T. Kaul (2008) provides extensive documentation. Here, we provide a few noteworthy examples.

Broadly when a labor retrenchment case goes to court it has to decide whether the aggrieved worker is entitled to protection of the IDA. For that, the court has to interpret what is an "industry" under the IDA. For example, are hospitals an industry and so are doctors and nurses protected from being fired? Second, the IDA protects "workmen" in an industry as opposed to managers. The question is who is a workman? Are airline pilots and software engineers workmen? Are contract workers eligible for protection although the IDA does not directly protect them?

One of the earliest such cases was the Hospital Mazdoor Sabha[9] case in 1960 that involved payment of retrenchment compensation to ward servants in JJ Hospitals, Mumbai. Initially,

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[8]In response to a query about this situation, the Union Labour Minister gave three reasons: "(i) Absence of affected parties at the time of the hearing; (ii) Seeking of frequent adjournments by the parties to file documents; and (iii) Parties approaching the High Courts challenging orders of reference issued by the appropriate government as well as orders issued by the Tribunals on preliminary points;..." (Sundar, 2020; Teamlease Services Report (2006) Link

[9]AIR 1960 SC 610

the Bombay high court dismissed the petition of the workers. Later when the case went to the Supreme Court, the management again pleaded that the Hospital was not involved in any trade or business. and hence, they are not an industry. The court framed a working principle that any systematic activity for production or distribution of goods or services done with the help of employees in the manner of a trade or business is an industry. The services in the hospital were held to be material services and hence it ruled that hospitals are "industry" under the IDA. However, the court went to contradict itself seven years later in a 1967 case involving Safdurjung Hospital[10]. Since "Safdurjung Hospital is not embarked on an economic activity which can be said to be analogous to trade or business. There is no evidence that it is more than a place where persons get treated. . . . It cannot, therefore, be said to be an industry..." Similarly, in a 1963 case[11] involving the University of Delhi in 1963 the court had ruled that educational institutions do not fall under the definition of industry. Over the years however, the court has changed its view and expanded the definition to cover "any economic activity . . . for production and/or distribution of goods and services calculated to satisfy human wants" even in the "absence of profit". Thus, philanthropies, educational institutions, government departments, public utilities and hospitals were no longer necessarily excluded from being an "industry".

One of the other contentious points has been determining who is a "workman". The act defines a workman to be "any person employed in any industry, to do any skilled or unskilled manual or clerical work, for hire or reward" excluding supervisors, managers and certain professions like the military and police. Since contract workers do not have direct contracts with the "firm" but are hired via a third-party contractor, it is assumed that they are not covered under the IDA. However, courts have differed in their judgments.

One of the earliest cases that dealt with this question was Shivnandan Sharma v. Punjab National Bank Ltd.[12] The Punjab National Bank shut down a particular branch office in

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[10](1970) 1 SCC 735. Safdurjung Hospital v. Kuldeep Singh
[11]AIR 1963 SC 1873. University of Delhi v. Ram Nath.
[12]AIR 1955 SC 404

November 1951. The bank had outsourced the management of the cash department to external treasurers. Mr. Shivnandan Sharma, the head cashier appointed and paid by the treasurers appealed to the court citing wrongful termination. In this case, the Supreme Court held that the treasurers and therefore their nominees are servants of the bank and therefore entitled to protection under the IDA.

The large country-made cigarette (beedi) industry in India employs a large army of non-regular workers who roll the cigarettes. Courts have differed in their judgement across cases within this industry as to whether these workers are "workmen" of the firm depending on the facts of each case. In Birdhichand Sharma v. First Civil Judge, Nagpur[13], the court ruled that although the workers were paid on a per piece basis, but because the workers did not have the freedom to work from home, their attendance was taken at the factory, they wouldn't be allowed to work if they came late and their products could be rejected if it did not meet standards, they were "workmen". In another case, Shankar Balaji Waje v. State of Maharashtra[14] merely since the worker was not bound to attend the factory for rolling cigarettes and had the freedom to come and go as he liked it was deemed that he is not a "workman". However, this judgement was passed by a majority vote of 2-1. The dissenting judge was of the view that since the management rejected products that were below a certain standard that established employer-workman relationship. This was used later while adjudicating the Mohideen Sahib & Sons v. Industrial Tribunal, Madras[15] case, where the workers had been hired via a third party contractor. It was held that the system of rejecting defective cigarettes established a supervisory role of the firm over the workers and thus the contractors were deemed to be mere managers of the firm. Hence, the court ruled the workers to workmen of the cigarette company under the IDA.

The disagreements between various Supreme Court justices have been far too frequent. In three cases in the late 1960s[16] the Supreme Court excluded workers not doing manual,

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[13]AIR 1961 SC 644

[14]AIR 1962 SC 517

[15]AIR 1966 SC 370

[16]May & Baker (India) Ltd. v. Workmen. AIR 1967 SC 678; Western India Match Co. Ltd. v. Workmen

clerical, supervisory or technical work from being "workmen". As against this, in a set of cases[17] in the early 1980s the court held that the workers whose job profile does not fall into one of the four categories cannot be necessarily excluded. From interviews we conducted with HR managers in leading tech firms and oil companies in India, the consensus that emerges is that it is hard to predict the outcome of labor disputes once they enter courts. Big companies usually try to offer high severance packages in order to disincentivize workers from going to court. However, financially distressed firms are in no position to do that. In summary, we conclude that the legal flexibility of hiring and firing labor in India is quite uncertain and hard to infer just from the letter of the law. Given common-law practices, the laws are open to interpretation by courts. The interpretation varies greatly over time, across states, and across industries and depends as much on the current polity and mood of the society. Along with the content, we suggest that the uncertainty surrounding the interpretation of the laws contributes to shaping exit costs.

2.3 Bankruptcy Laws

Unsurprising like labor laws, bankruptcy laws were also derived from English laws. In India, the necessity for an insolvency law was first felt in the three Presidency towns of Calcutta, Bombay and Madras where the British carried on their trade. The earliest rudiments of insolvency legislation can be traced to Sections 23 and 24 of the Government of India Act, 1800 (39 and 40 Geo. III c. 79), which conferred insolvency jurisdiction on the Supreme Court at Fort William and Madras and the Recorder's Court at Bombay. The enactment of Statute 9 (Geo. IV c. 73) in 1828 is understood to be the beginning of the special insolvency legislation in India. The British later enacted Presidency Towns Insolvency Act, 1909 to deal with insolvency in the Presidency towns and the Provincial Insolvency Act, 1920 for other places. Bankruptcy proceedings for individuals even today is regulated under these

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(1964) 3 SCR 560; and Burmah Shell Oil Storage & Distribution Co. of India v. Burmah Shell Management Staff Association (1970) 3 SCC 378

[17]S.K. Verma v. Mahesh Chandra, (1983) 4 SCC 214; Ved Prakash Gupta v. Delton Cable India (P) Ltd. (1984) 2 SCC 569; and Arkal Govin Raj Rao v. Ciba Geigy India Ltd. (1985) 3 SCC 371

two acts.

Historically though the enforcement of creditor rights in India has been met with significant judicial delay. Partly this has been because insolvency procedures have been complex and fragmented across multiple legislations like the Companies Act, 1956 and the Sick Industrial Companies (Special Provisions) Act, 1985. Since the early 90s, governments have attempted various reforms with limited success. In 1993, for example Debt Recovery Tribunals (DRTs) were setup. These were quasi-judicial institutions that streamlined the legal process and allowed speedy adjudication and swift execution of judgements (Visaria 2009). However, overtime shortage of infrastructure and recovery personnel ended up clogging these tribunals. Legal loopholes also allowed firms to file cases using alternate routes to stall the banks from recovering their debts.

A major reform came in 2002 when the Indian government enacted the Securitization and Reconstruction of Financial Assets and Enforcement of Security Interests Act (SARFAESI). This permitted secured creditors to take possession of secured assets within 60 days of notice on a non-performing asset loan, allowing them to circumvent the lengthy judicial process. SARFAESI was a huge success initially (Kulkarni, 2021). However, overtime as courts have interpreted and reinterpreted the Act, its power has gotten diluted. For example, now the law permits the borrowers a right to appeal – a measure that dilutes loan recovery. There has been lack of clarity regarding the boundaries of jurisdiction. Once a bank starts recovery proceedings under the SARFAESI Act, high courts cannot intervene. However, High Courts often stay recovery proceedings, requiring intervention by the Supreme Court delaying the process.[18]

Another issue with SARFAESI is that there is no clear guidelines on the order in which debts have to be paid when a firm defaults. There were separate laws that defined the rights of secured creditors, unsecured creditors and operational creditors in the event of default by the firm and these involved proceedings in multiple fora. With one forum deciding on the

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[18]Singh, S."SC asks HCs not to interfere with debt recovery proceeding", The Economic Times, Aug 3, 2010. [Link].

rights of one category of creditors and another deciding on the rights of a competing party, decisions are usually appealed against in the higher courts and they would get stuck there.

An excerpt from Ravi (2015) highlights the extent of the problem:

"The case of BHEL v. Arunachalam Sugar Mills ("ASM") that was decided by the Madras High Court in 2011 provides a good illustration of this. ASM and its sister concern defaulted on their credit facilities which gave rise to numerous proceedings by secured and unsecured creditors alike. A bank, the main secured creditor, filed an application in the Debt Recovery Tribunal for debt recovery. Another creditor filed a petition under the Companies Act, 1956 for the winding up of ASM......... A company that had leased machinery to ASM, initiated proceedings invoking the arbitration clause in the agreement and filed an application in the High Court restraining ASM from transferring/ selling its assets. A secured creditor of ASM's sister concern initiated proceedings under SARFAESI Act, took possession of its assets and sold the same by auction. An unsecured creditor, which had supplied a boiler to ASM, filed a civil suit against ASM for recovery of money due to it by sale of immovable properties of ASM........While this might be at the extreme end of the spectrum in terms of the number of parallel proceedings, almost all of the cases reviewed involved proceedings in at least two fora and more often than not proceedings going on in parallel."

Courts also do not have the expertise to distinguish between viable and non viable firms. They usually follow a pro-debtor stance and they are reluctant to order the liquidation of non viable businesses (Ravi, 2015; BLRC Report, 2015[19]). Thus, even with SARFESI large cases took an average of 6 years to resolve (Sengupta, Sharma, Thomas, et al., 2016) and recovery rates averaged 26% – among the lowest in the world (Patel 2020). As a result, resources get trapped in inefficient firms which could adversely affect manufacturing TFP.

In 2016, by enacting the Insolvency and Bankruptcy Code (IBC) the government tried to streamline things further. Most importantly, the act changed the judicial stance from "debtor in possession" to "creditor in possession" of assets as soon as the creditor initiates insolvency

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[19]See the [Link]

proceedings. The IBC tried to replace many overlapping provisions in various previous laws and most importantly extended beyond secured creditors to unsecured creditors and non-banking financial companies. Under this law, once a case is admitted to the National Company Law Tribunal (NCLT), a resolution professional and trustee are appointed who takes possession of assets. Resolution plans are solicited from prospective buyers which the creditor's committee can select from by a super-majority vote. If no plan is selected, liquidation procedures commence.

However, even the IBC has very limited success due to several judicial bottlenecks and court congestion[20]. Despite these issues, there is little work on the extent of exit barriers and how these vary across states, and the effect they seem to have on firms, firm dynamics, and productivity in India.

3 Data

We need to have data at the firm level and information on when firms enter and exit. Our main data source is the Annual Survey of Industries. This is a nationally representative sample survey of manufacturing establishments in India collected by the government. We use the panel version of this dataset which is available since 1998. A major shortcoming of this data is that of missing information. Since smaller firms (less than 100 workers) are not sampled every year, and because there are non-compliers (establishments that do not respond to the survey) the panel is an unbalanced one. Despite this shortcoming, the data has many attractive features. First, entry is easy to measure as for each establishment, the survey records its initial year of production. Second, the data also record the status of the responding establishments as either "active" or "dormant". "Dormancy" is a state where the firm exists with all its capital and labor but does not engage in production. This is an important feature. It reflects high exit barriers–establishments that want to exit but cannot

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[20]For a vivid account read India is No Country for Dying Firms by Andy Mukherjee in The Washington Post (Aug 23, 2021) [Link] and Three years later, India's bankruptcy reform languishes in courts in the Reuters (Jan 27, 2019) [Link]

and hence stay dormant. Finally, by tracking the mass of establishments of a certain vintage over time, we can build credible measures of exit (following Hsieh and Klenow (2014)). We exploit these features in our analysis to estimate exit costs.

For robustness, we also use the PROWESS data collected by the Center for Monitoring of the Indian Economy (CMIE) which comes from the balance sheets and income statements of large publicly traded companies that by law have to make this information publicly available. There are issues with using this data. First, the location of the "company" is that of the headquarter which could be totally different from the establishment we are interested in. To the extent we want to compare exit barriers across different states, this aspect of the data makes such a comparison infeasible. Second, when a company "appears" in or "disappears" from this dataset is unclear as this could happen because of actual exit or merely exit from the dataset.

4   Motivating Facts

We begin by presenting a novel set of facts that suggest that exit costs are both large and differ across states and that the way manufacturing firms respond to these frictions is in line with simple theory.

Fact 1: Exit rates are low in India

While there is no direct measure of exit available in either the PROWESS or ASI data, we use a novel approach due to Hsieh and Klenow (2014) to measure exit rates overall and at the state-industry level. From any survey round, we can calculate the number of establishments of a specific vintage (dating to the initial year of production). Since the sample is representative, the only reason why the survey in year $t + \Delta$ would give a lower number of firms of a certain vintage as compared to when we use the sample from the survey in year t is because some firms have exited. This approach allows us to estimate exit rates

within each state-industry cell.

Figure 1a shows that not only is firm exit (using ASI data) in the manufacturing sector in India lower than that in advanced economies like the United States, but it is also lower relative to the smaller economies of Bangladesh and Vietnam. Figure 1b (using PROWESS data) shows that firm exit has been low over the last decade across all sectors, and exit in manufacturing has been consistently lower than in IT services which comprises one of the more dynamic sectors of the Indian economy. The great recession, which hit India a little later than the US, raised exit rates considerably, but by 2015, they were back to their pre-recession levels.
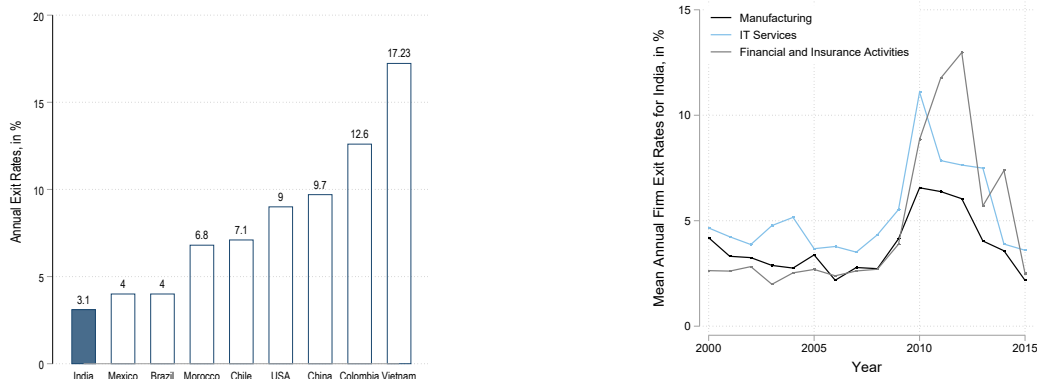
(a) Exit Rates in the Manufacturing Sector   (b) Exit Rates across sectors (CMIE Data)

Figure 1: Firm Exit Rates

Notes: Panel (a): Exit rates of different countries have been calculated/taken from the following sources: India - calculated from Annual Survey of Industries dataset from survey years 2000-01 and 2015-16; Brazil and Mexico - taken from Bartelsman, Haltiwanger, and Scarpetta (2009) averaged from 1990-1999; Chile, Colombia and Morocco - taken from Roberts and Tybout (1996) for the year 1985; US - taken from figure 1 in "Business Exit During the COVID-19 Pandemic: Non-Traditional Measures in Historical Context" by Crane, Decker, Flaaen, Hamins-Puertolas, and Kurz (2022) for 2006; China - calculated from Annual Surveys of Industrial Production for 2006; Vietnam - calculated from Vietnam enterprise census for 2007.

Fact 2: Entry shares and exit shares are highly correlated

We begin by documenting that there is significant variation in manufacturing activity across Indian states. To illustrate this, we compute plant entry shares in major states of India.[21] We

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[21]We exclude North-Eastern states, Jammu and Kashmir, and Goa from our analysis because the sample data is very sparse.

define entry share of a state in a given year as the number of plants that enter the state that year divided by the total number of entrants in India for that year, normalized by the state's population share. Thus, if a state's entry share is greater (lower) than 1, then it attracts more (fewer) entrants relative to its size. The left panel of figure 2b plots entry shares of states averaged from 1999 to 2018, with the darker (lighter) shades of blue representing states with average entry shares greater (lower) than 1. It is immediately apparent that some states are disproportionately more attractive to industries relative to their size. In particular, entry into the states of Gujarat, Maharashtra, Andhra Pradesh, Karnataka, and Tamil Nadu are higher than that to the more populous Northern states of Uttar Pradesh, Madhya Pradesh, Rajasthan, Bihar and West Bengal. Moreover, as shown in figure ??, the spatial variation in entry shares has been persistent over time. This implies the existence of underlying structural factors driving plant entry that have remained unchanged.

As noted earlier, institutional features shape barriers to exit for plants in India, and institutions vary considerably across states. Thus, spatial variation in exit barriers faced by plants could be a reason why some states are more attractive to potential entrants than others. Intuitively, if a state has high exit barriers, then potential entrants would be discouraged to enter because of lower ex-ante expected profits.

The right panel of figure 2b shows the relationship between entry and exit shares of states. We calculate state-wise exit shares in two steps. First, within each state, we define exit share for each age cohort as the mass of plants that exited from the cohort in that state divided by the total mass of plants that exited from the cohort in India. Exit share of a state is, then, the weighted average of state-cohort wise exit shares, with the fraction of plants belonging to each cohort in the state as weights. To facilitate comparison with entry shares, we normalise exit share of a state with the state's population share. As with entry shares, a size-adjusted exit share of 1 is considered to be neutral. Figure 2b displays clear sorting – states with higher exit shares, represented in black, have higher entry shares, and vice-versa.

For the analysis that follows, we classify states with average entry share above 1 as 'good'

and those below 1 as 'bad'.[22]

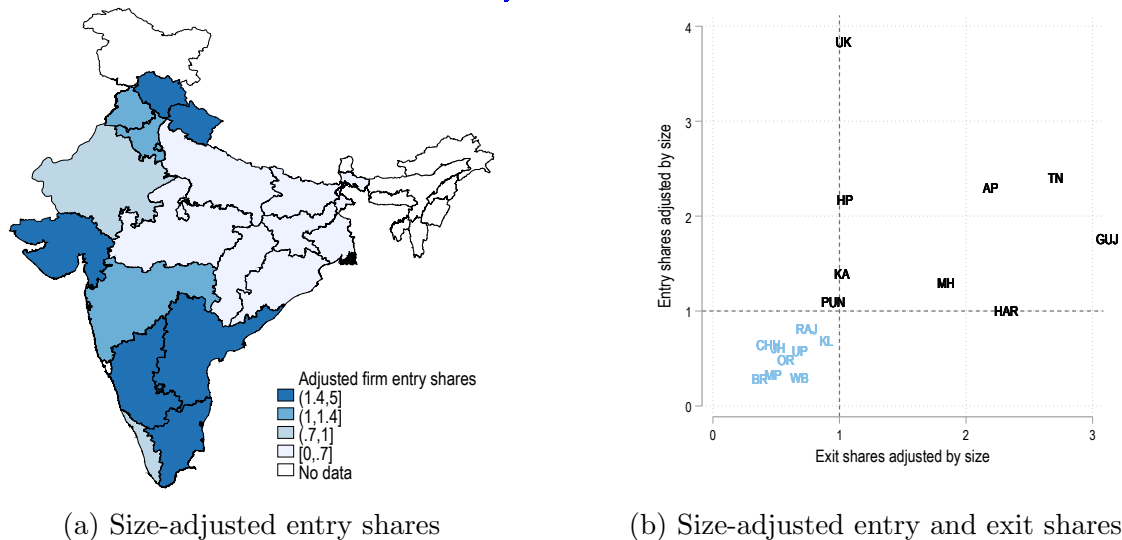(a) Size-adjusted entry shares

(b) Size-adjusted entry and exit shares

Figure 2: Size-Adjusted Entry and Exit Shares Across States

Notes: Size-adjusted entry share of state s at time t: entry share of state s at time t normalized by its population share. Analogously, size-adjusted exit share of state s: exit share of state s normalized by its population share. Panel (a) shows size-adjusted firm entry shares in Indian states averaged from 1999 to 2016. Good states are those with size-adjusted entry share greater than 1 (the two darker shades of blue). Bad states are those with size-adjusted entry shares less than or equal to 1 (lighter shades of blue). Panel (b) shows the relationship between size-adjusted entry and exit shares for states. The relationship between un-adjusted entry and exit shares is in Figure 12.

Fact 3: Exit rates are higher in good states than in bad states

Next we compute annual exit rates by age cohort to rule out the possibility that low (high) exit shares might merely reflect the fact that bad (good) states have fewer (more) plants. To be precise, we calculate the mass of plants that exited for each state group-cohort, and normalize it with the initial mass of plants. The left panel of Figure 3 shows that exit rates are lower in bad states across cohorts of plants of different ages. Among old plants, especially, exit rates are much higher in good states compared to bad states.

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[22]We choose not to use the labor regulation index of Besley and Burgess (2004) as it captures only labor-related frictions. It is worth noting that entry shares, as we define them, are negatively related to labor unrest measures as might be expected. This is shown in Figure 13 in the Appendix.
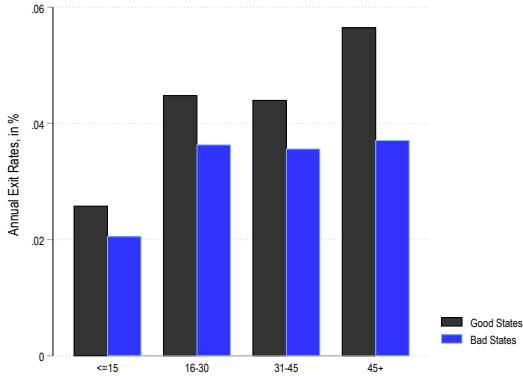
(a) Exit Rates in Bad vs Good States
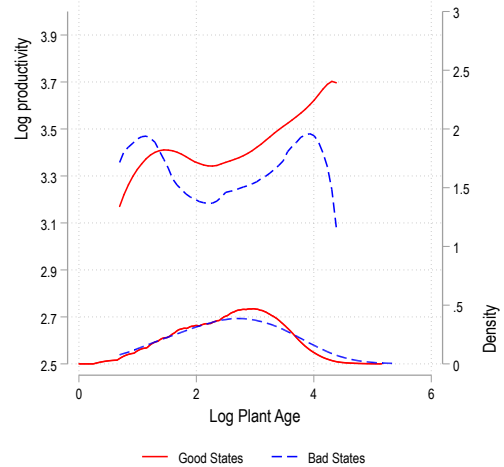
(b) Productivity versus Age

Figure 3: Bad vs Good States: Annual Plant Exit Rates and Manufacturing TFP
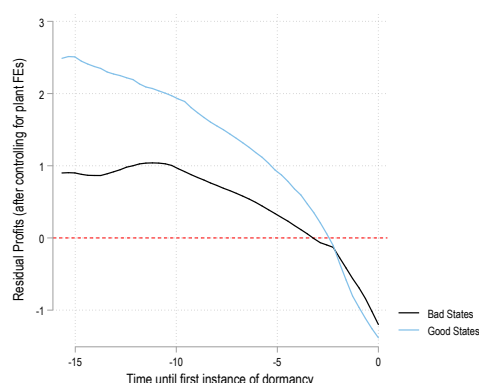
Fact 4: Productivity is lower in bad states

The consequence of exit costs can be seen in the productivity distribution of plants. We follow Hsieh and Klenow (2009) and calculate plant productivity as a Solow residual from the production function. The right panel of Figure 3 examines the cross-sectional relationship between plant productivity and plant age (left axis), as well as the age distribution of plants (right axis). Because of greater dynamism, as expected, on average, plant productivity is higher in good states by about 22 percent. More important, we show two non-trivial consequences of exit costs in Figure 3b. First, since exit barriers act as entry barriers, there is stronger selection in bad states – productivity is higher among young plants as only the better plants are able to enter bad states. Second, as plants age, unproductive plants in bad states do not exit and hence productivity falls precipitously in bad states. This results in a right tail of really old plants with very low productivity in bad states. Such plants are absent in good states.

Fact 5: Dormancy is a Pathway to Exit for Plants

While we do not observe with certainty whether a plant in ASI data has exited, we do observe them in three states – actively producing, dormant with workers (those existing with fixed assets and maintaining staff but not actively producing)[23], and dormant without workers (those existing with fixed assets but not maintaining staff and not producing)[24]. As illustrated with the case study on Nokia's factory in Tamil Nadu, plants enter long periods of dormancy before exiting. During this period, they make various adjustments like obtaining government permissions and laying off workers, i.e. moving toward exit, while production is at a standstill.
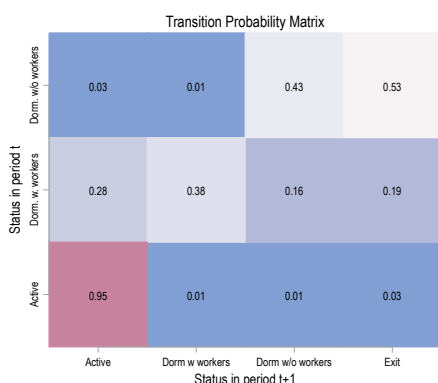
(a) Transition Probability Matrix   (b) Profits as they approach dormancy

Figure 4: Dormancy as a Pathway to Exit for Plants

Notes: The left panel calculates the probability with which a plant that is in state i in period t (where i ∈ {Active, Dormant with workers, Dormant without workers}) transitions to state j in period t+1 (where j ∈ {Active, Dormant with workers, Dormant without workers, Exit}). The right panel shows plant profits, deflated by sales, as they approach the first instance of either kind of dormancy. To plot the right panel, we first residualize the y-variable and x-variable of plant fixed effects. Second, we re-scale the residuals by adding back the unconditional sample means of the respective variables. Third, we divide observations into 20 equally sized bins based on their x values and calculate the mean of y and x values within each bin. The solid lines above are a polynomial fit of the resulting mean values.

    The left panel of Figure 4 shows transition probabilities of plants between the different

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[23]As per the ASI survey manual, for these units "it is found during the survey that the unit existed in the given location and had engaged some employees during the reference period, but could not initiate production or did not produce anything during the reference period due to various reasons, and can take up production any moment once the problems are sorted out."

[24]The ASI survey manual categorizes these units as those "which existed in the given location, but did not engage any employee during the reference period, and also, did not initiate production or produce anything during the reference period."

states. Of the plants that are active in any period, the probability that they continue to remain active is very high (=95%), and this points indirectly to the low chances of exit. A small fraction transitions to dormancy or exits. Some dormant plants with workers transition back to being active, implying that they might have stopped production due to a temporary shock and would restart production soon. But a large fraction of them either continue to stay dormant with workers, or transition to laying-off workers and finally exiting. However, after entering dormancy without workers, it is highly unlikely that the plant ever restarts production. We constructed the left panel of figure 4 by focusing on plants in the census sector, and pooling data from 1999 to 2007. We classify a plant to have exited here if it does not show up in the data after 2007[25]. Based on these transition probabilities, we postulate that dormancy is a path to exit for plants.

Plants enter dormancy as a result of losses. The right panel of Figure 4 plots profits of active plants as they approach dormancy. Two aspects are worth noting. First, on average, plants in bad states make lower variable profits than plants in good states. Second, plant profits fall as they approach dormancy, and variable profits turn negative before they become dormant, slightly earlier in bad states. Note that fixed costs are not included in variable costs so firms would be making lower profits than indicated by their variable profits alone.

Fact 6: Firing costs for regular workers are higher in bad states

In this section, we examine whether labor adjustment is harder in bad states than in good states by comparing how plants in different states adjust labor in response to similar shocks to plant performance. We follow Guiso, Pistaferri, and Schivardi (2005), Fagereng, Guiso, and Pistaferri (2018), and Contractor (2022) to isolate unanticipated changes in gross value added (GVA) that cannot be explained by plant-specific characteristics and aggregate fluctuations.

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[25]Since we have data until 2018, we check if they show up again in the data in the next 11 years. If a plant stops showing up in the data, it could be because it has exited or hasn't complied with data reporting, or it was just dropped from the sample. However, exit is highly likely for the census sector plants, conditional on having observed a plant once and then not observing it for at least the next 11 years.

In particular, we regress the inverse sine transformation of GVA[26] on a plant (λ_i), an industry-year (λ_{jt}), and a state-year (λ_{st}) fixed effect. This regression's residuals, r_{ijst}, capture the unanticipated shocks to a plant's GVA

$$\text{IHS}(GVA_{ijst}) = \lambda_i + \lambda_{jt} + \lambda_{st} + r_{ijst}.$$

Next, we want to estimate how plants adjust their employment when faced with negative shocks. Hence, first, we define a dummy variable $\mathbb{1}\{Negshock_{it}\} = 1$ whenever $r_{ijst} < 0$, and 0 otherwise. Then we use the following difference-in-differences specification to compare employment adjustment in plants facing similar shocks but located in different states.

$$Y_{ijst} = \alpha_i + \alpha_{jt} + \alpha_{st} + \gamma'\mathbf{X_{ijst}} + \beta_1\mathbb{1}\{Negshock_{it-1}\} + \beta_2\mathbb{1}\{Negshock_{it-1}\} \times \mathbb{1}\{Bad_s\} + \epsilon_{ijst}$$

$$(1)$$

The outcomes of interest here are logarithms of regular employment, contract employment, and managerial employment at the plant level. $\mathbb{1}\{Bad_s\}$ is a dummy variable that takes a value equal to 1 if the plant is located in a bad state. In order to minimize omitted variable bias, we incorporate a rich set of covariates that are both time-invariant and time-varying in the regression specification. In particular, plant fixed effects (α_i) account for time-invariant unobserved heterogeneity at the plant level. α_{jt} and α_{st} control for factors that are common across plants but vary at the industry-year, and state-year level respectively. $\mathbf{X_{ijst}}$ is a vector that includes size-year fixed effects, which account for differential trends by firm size, and other time-varying plant-specific characteristics such as their share of contract workers and capital in the previous year.

With these controls, β_1 measures the average impact of negative shocks on employment in the subsequent year by plants in good states. β_2 captures the differential response to

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[26]We take the IHS instead of log because in the data GVA is sometimes negative. Results are consistent if we re scaled GVA to be positive.

negative shocks in bad states. Since the set of controls includes industry-year and size-year fixed effects, β_1 and β_2 are identified by comparing similar-sized plants within the same industry.

Table 1: Impact of negative shocks on employment in good and bad states

Dependent variable:	log Employment					
	(1)	(2)	(3)	(4)	(5)	(6)
	Regular Workers	Regular Workers	Contract Workers	Contract Workers	Managers	Managers
$\mathbb{1}\{Neg\_shock_{it-1}\}$	-0.155***	-0.167***	-0.168***	-0.169***	-0.120***	-0.129***
	(0.007)	(0.009)	(0.015)	(0.02)	(0.006)	(0.008)
$\mathbb{1}\{Neg\_shock_{it-1}\} \times \mathbb{1}\{Bad_s\}$		0.029*		0.002		0.021
		(0.014)		(0.031)		(0.011)
N	165219	165219	61942	61942	157836	157836

All regressions contain plant, industry-year, state-year, and size-year fixed effects. Robust standard errors clustered at the plant level in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2: Heterogeneous impact of negative shocks on employment in good and bad states

Dependent Variable:	Log Employment			
	(1)	(2)	(3)	(4)
	Regular Workers	Regular Workers	Contract Workers	Managers
$\mathbb{1}\{Neg\_shock_{it-1}\}$	-0.185***	-0.185***	-0.169***	-0.135***
	(0.01)	(0.01)	(0.02)	(0.009)
$\mathbb{1}\{Neg\_shock_{it-1}\} \times \mathbb{1}\{Bad_s\}$	0.016	0.016	-0.018	0.018
	(0.016)	(0.016)	(0.034)	(0.013)
$\mathbb{1}\{Above100_{it-1}\}$	0.514***			
	(0.011)			
$\mathbb{1}\{Neg\_shock_{it-1}\} \times \mathbb{1}\{Above100_{it-1}\}$	0.05***	0.052**	0.003	0.017
	(0.019)	(0.019)	(0.041)	(0.016)
$\mathbb{1}\{Bad_s\} \times \mathbb{1}\{Above100_{it-1}\}$	0.076***	0.074***	-0.076	0.05**
	(0.021)	(0.021)	(0.040)	(0.016)
$\mathbb{1}\{Neg\_shock_{it-1}\} \times \mathbb{1}\{Bad_s\} \times \mathbb{1}\{Above100_{it-1}\}$	0.076***	0.078**	0.055	0.026
	(0.029)	(0.029)	(0.066)	(0.027)
N	165219	165219	61942	157836
Size-Year FE	No	Yes	Yes	Yes

All regressions contain plant, industry-year, and state-year fixed effects. Robust standard errors clustered at the plant level in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 1 reports estimates of β_1 and β_2 from specification (1). Column 1 of table 1 indicates that plants reduce their regular employment by 15.5% on average when faced with a negative shock in the previous year. However, plants in bad states are less sensitive to these shocks, as shown in column 2 below. In particular, a negative shock reduces average

regular employment in the subsequent year by only 13.8% in bad states, compared to 16.7% in good states. Columns 3 and 5 show that a negative shock reduces average contract and managerial employment in the subsequent year by 16.8% and 12%, respectively. There is no statistically significant difference between how good and bad states adjust their contract and managerial employment in response to negative shocks.

The labor laws make firing particularly hard for firms employing more than a hundred workers. Therefore, next, we show that the labor adjustment frictions in bad states are precisely coming from the larger plants. To do so, we define a dummy variable $\mathbb{1}\{Above100_{it}\}$ that equals 1 for plants employing more than 100 workers in year t and is 0 otherwise. Then we estimate a triple differenced version of the model above (1), essentially interacting each co-variate with $\mathbb{1}\{Above100_{it-1}\}$. Column 1 of table 2 shows that primarily the large plants, those with more than 100 regular workers, drive the sluggish response to negative shocks in bad states.

Fact 7: Inflation helps in shedding regular workers, and more so in bad states.

As plants approach dormancy, they lay off workers – regular, contractual, and managers – as shown in panel (a) of figure 14. Although adjustment of regular workers is hard because of labor regulations, plants still lay them off as they approach dormancy. How do they do it? We argue that one channel that they use to adjust labor is inflation. Plants on the path to dormancy, especially those in bad states and in high inflation periods, will want to incentivize attrition of regular workers by keeping nominal wages fixed, which makes outside options more attractive. Hence, we should see a larger fall in regular workers when a plant approaches dormancy in high inflation periods relative to low inflation periods, and more so in bad states than in good states. Moreover, if inflation is being used by plants as a tool to adjust labor that is otherwise harder to fire, we should not see this pattern for contract workers or managers.

We look for employment effects by estimating the following specification.

$$Y_{ijst} = \beta_0 + \sum_b \beta_1^b \, (D - t)_{ijst}^b + \beta_2^b \, (D - t)_{ijst}^b \times \mathrm{HI}_t$$

$$+ \mathbf{X}_{ijst}' \delta + \lambda_i + \lambda_{st} + \lambda_{jt} + \epsilon_{ijst},$$

The outcomes of interest are logarithms of regular employment, contract employment, and managerial employment for plant i in industry j, state s at time t. $(D - t)_{ijst}$ are the years until the first instance of either kind of dormancy for the plant. This is divided into four bins $b \in \{> 6\text{years}, 5 - 6\text{years}, 2 - 4\text{years}, 1\text{year}\}$. > 6 years is the omitted category. HI_t is an indicator that takes value 1 if the annual percentage change in CPI is greater than 5%. $\mathbf{X_{ijst}}$ is a vector of plant level, time-varying observable characteristics like plant age, age squared, and book value of assets in the previous year. We also include plant fixed effects λ_i, state-year fixed effects denoted by λ_{st}, and industry-year fixed effects denoted by λ_{jt}.

The regression results on employment are reported in Figure 5. The left panel corresponds to logarithm of regular workers, the middle panel corresponds to logarithm of contract workers, and the right panel corresponds to logarithm of managerial staff. The black and blue lines plot predicted estimates from the regression, and the vertical bars represent 95% confidence intervals. If the upper limit of the CI is below the blue line then β_2 must be significant, i.e. high inflation has a differential impact on the outcome variable of interest.
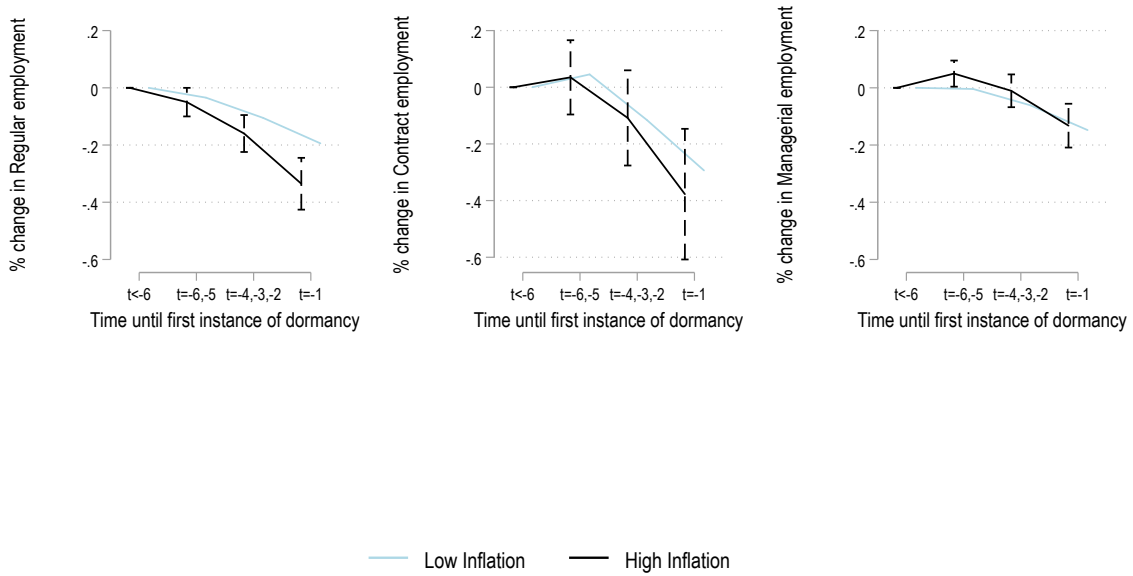
Figure 5: Labor Adjustment and Inflation

Figure 5 shows that manufacturing plants in India on the path toward dormancy reduce employment–regular, contract, and managers. Compared to 6 years prior to dormancy, these plants have 33.5% fewer regular workers, 37.7% fewer contract workers, and 13.2% fewer managers in the year just prior to dormancy. There is a differential response in this labor adjustment process only for regular workers. Plants are likely to reduce 14.1% and 5.4% more regular workers in the year prior and 2-4 years prior to dormancy during high inflation years as compared to normal years.

Next, in Figure 6, we show that this differential adjustment of regular workers during high inflation periods primarily happens in bad states where presumably labor adjustment costs are much higher.[27] We find no differential effects for contract workers and managers between good and bad states (see Figures 15 and 16).

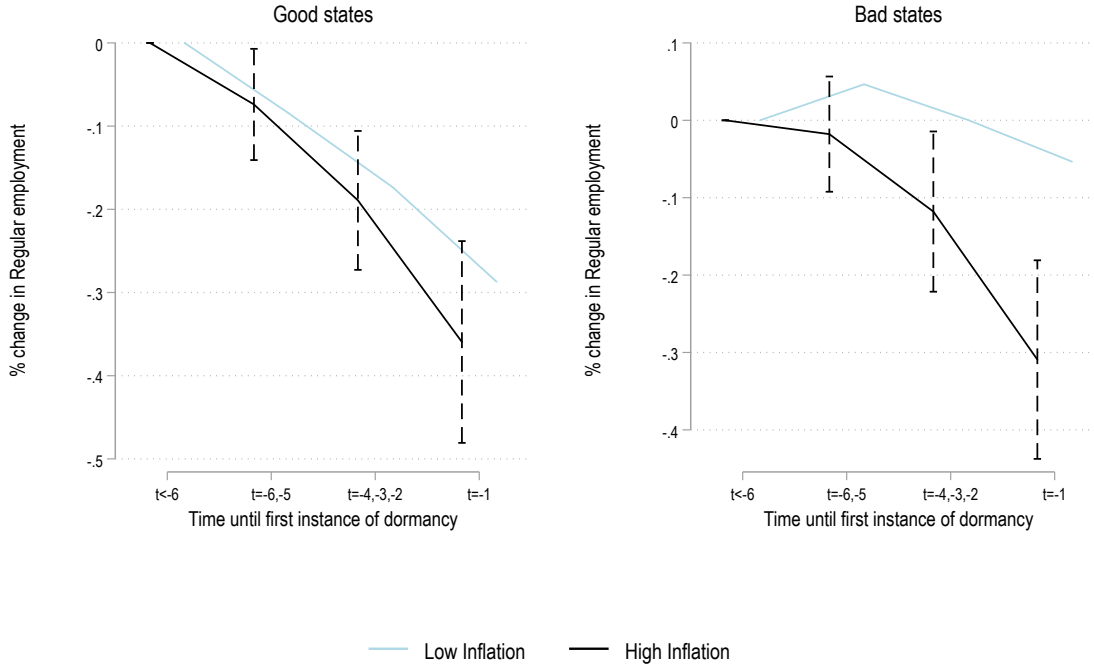[27]We introduce triple interactions in the regression model with an indicator for bad states.

Figure 6: Adjustment of Regular Workers and Inflation

5 Model

In this section, we develop a theoretical model to estimate exit frictions and quantify the implications for aggregate productivity. Our framework builds on the models of firm dynamics (see Roberts & Tybout, 1997, Melitz, 2003, Das et al., 2007 and Aw, Roberts, & Xu, 2008), models of labor market frictions (see Hopenhayn & Rogerson, 1993, Poschke, 2009, Cooper & Willis, 2009 and Cooper & Haltiwanger, 2006) and models of exit (see Ryan, 2012, Dunne, Klimek, Roberts, & Xu, 2013, Ryan, 2012, Golombek & Raknerud, 2018).

In our model, firms are heterogeneous in their productivity which evolves over time. We divide firms' decision making into a static component, where the firms maximize their short-run profits by sourcing intermediate inputs, and a dynamic component where they make decisions on production in the presence of fixed costs, choosing dormancy or exit in the presence of exit costs, and adjust their labor and capital knowing there exist convex

adjustment costs on both the up and down side.

We model two frictions in the economy that distort resource allocation. First, due to convex labor firing costs, firms with low productivity shed labor gradually, which distorts the labor allocation away from efficient firms. Second, due to convex firing costs as well as exit costs, firms tend to stay in the market in a dormant state for an extended time as they search for a path to exit. They gradually reduce their labor employment as this both reduces labor firing costs and gives them the option to restart production in the future without incurring large hiring costs or setup costs. [28] The existence of these dormant firms, also sometimes called Zombie firms, prevents scarce resources, such as capital and land from reallocating to more productive firms. We construct and estimate our structural model using ASI data to help us understand and quantify the extent of such misallocation in the economy.

We adapt the indirect inference estimation strategy from Golombek and Raknerud (2018) to estimate model parameters. Their method solves the main difficulty of simulation-based inference in structural discrete–continuous choice models, namely that the simulated trajectories are discontinuous functions of the structural parameters. This is important for us as we need to have both elements, labor and capital choice as the continuous choices and exit which gives a scrap value. This scrap value, which could be negative, is key for us. Low scrap values suggest the presence of significant exit costs.

5.1 Production

Firms are heterogeneous in their productivity ϕ_{it}, where i denotes the firm and t denotes the time. Firm productivity ϕ_{it} evolves over time following an AR(1) process with coefficient γ_1.

$$\ln \phi_{it} = \gamma_0 + \gamma_1 \ln \phi_{it-1} + \varepsilon_{it}$$

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[28]However, it is difficult to rationalize dormancy, especially dormancy without workers in this manner. From what we see in the data, a tiny fraction of firms which are removed from the data for being dormant without workers, reappear afterward.

Firms use labor, capital and intermediate inputs in their production. Labor is of two types, regular workers (L_{rt}) and non-regular labor (L_{ct}) which are imperfectly substitutable. Both types of labor are subject to hiring and firing costs. We grouping managerial workers in with contract workers and other workers as all of these are easier to adjust, given labor laws, than regular workers.[29] In addition, firms can adjust their capital K_t subject to convex adjustment costs. Intermediate inputs I_t are chosen freely every period.

We assume a Cobb-Douglas production function.

$$Y_{it} = \phi_{it} L_{it}^{\alpha_L} I_{it}^{\alpha_I} K_{it}^{\alpha_K} \qquad \alpha_L + \alpha_I + \alpha_K = 1$$

where,

$$L_{it} = L_{c,it}^{\alpha_{Lc}} L_{r,it}^{\alpha_{Lr}}$$

We assume that the per period input prices are r_I and w_c, w_r, for intermediate inputs, regular and non-regular workers, respectively, and these prices are exogenously given.

5.2 Static Decisions

Firms engage in monopolistic competition and face a demand function with constant elasticity σ,

$$D(p) = p^{-\sigma} E$$

where E is the aggregate demand normalized to 1 and p is the price charged by the firm.

In each period, given labor employment, L_{ct}, L_{rt}, and capital, K_t, firms make a static

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[29]This grouping also makes it easier to deal with the fact that many firms have no contract workers which causes problems (zero use of any kind of factor will give zero output given our setup).

decision to maximize profits by choosing intermediate inputs and price.

$$\max_{I_{it},p} \quad p^{1-\sigma}E - r_I I_{it}$$

$$\text{s.t.} \quad p^{-\sigma}E = \phi_{it}L_{it}^{\alpha_L}I_{it}^{\alpha_I}K_{it}^{\alpha_K}$$

Therefore, the per period value added as a function of L_{ct}, L_{rt}, and K_t takes the following function form.

$$VA(\phi_{it}, L_{c,it}, L_{r,it}, K_{i,t}) = \left(1 - \alpha_I \frac{\sigma-1}{\sigma}\right)\left(r\alpha_I \frac{\sigma-1}{\sigma}\right)^{\frac{\alpha_I \frac{\sigma-1}{\sigma}}{1-\alpha_I \frac{\sigma-1}{\sigma}}} \left(E^{\frac{1}{\sigma-1}}\phi_{i,t}L_{i,t}^{\alpha_L}K_{i,t}^{\alpha_K}\right)^{\frac{\frac{\sigma-1}{\sigma}}{1-\alpha_I \frac{\sigma-1}{\sigma}}} \quad (2)$$

The per period value added of firm i is increasing in its productivity ϕ_{it}, labor employment L_{it} and capital K_{it}.

Let $\tilde{\phi}_{it}$ be the profitability of firm i at t, $\tilde{\phi}_{it} = \left(1 - \alpha_I \frac{\sigma-1}{\sigma}\right)\left(r\alpha_I \frac{\sigma-1}{\sigma}\right)^{\frac{\alpha_I \frac{\sigma-1}{\sigma}}{1-\alpha_I \frac{\sigma-1}{\sigma}}} \left(E^{\frac{1}{\sigma-1}}\phi_{i,t}\right)^{\frac{\frac{\sigma-1}{\sigma}}{1-\alpha_I \frac{\sigma-1}{\sigma}}}$.

The evolution of profitability to be estimated is the following.

$$\ln\tilde{\phi}_{it} = \tilde{\gamma}_0 + \tilde{\gamma}_1 \ln\tilde{\phi}_{it-1} + \tilde{\varepsilon}_{it} \quad (3)$$

5.3 Dynamic Decisions

5.3.1 Labor Adjustment and its Costs

As shown previously, labor adjusts gradually, which indicates convex labor adjustment costs. We assume labor adjustment cost are quadratic. Let $\bar{L}_{ct}$ and $\bar{L}_{rt}$ be the targeted employment level chosen by firms. When $\bar{L}_{ct} > L_{ct-1}$ or $\bar{L}_{rt} > L_{rt-1}$, firms pay a convex hiring cost $H_c \times (\frac{\bar{L}_{ct}}{L_{ct-1}} - 1)^2$ or $H_r \times (\frac{\bar{L}_{rt}}{L_{rt-1}} - 1)^2$. The hiring cost captures the fact that it is costly for firms to post vacancies, find and hire the best-qualified workers. The quadratic form captures the fact that it is harder to hire a larger percentage of workers at one time. As regular and non-regular workers are different and employed through different channels, the

hiring costs are potentially different. We assume

$$H_r = \bar{H}_r + c_{Hr}L_{r,t-1} \tag{4}$$

$$H_c = \bar{H}_c + c_{Hc}L_{c,t-1} \tag{5}$$

This allows the convexity of hiring costs of both regular and non-regular workers to increase or decrease with the size of last periods labor force.

Firing costs are meant to capture the frictions rising from both size based labor laws and the presence of strong labor unions in India. If firms wish to fire workers, i.e., the targeted labor force lies below the exiting level, it incurs costs. This is especially so for regular workers and for firms that employ more than 100 regular workers during our sample period. Therefore, we model different firing costs for large vs small firms, i.e. $F_r^L \times (\frac{\bar{L}_{rt}}{L_{rt-1}} - 1)^2$ for firms with regular workers fewer than 100, and $F_r^H \times (\frac{\bar{L}_{rt}}{L_{rt-1}} - 1)^2$ for firms with regular workers more than 100.

$$F_r = \begin{cases} \bar{F}_r^L + c_{Fr}^L L_{r,t-1} & \text{if } L_{r,t-1} \geq 100 \\ \bar{F}_r^S + c_{Fr}^S L_{r,t-1} & \text{if } L_{r,t-1} < 100 \end{cases} \tag{6}$$

For non-regular workers, firms pay a convex firing cost to lay off contract workers as well when $\bar{L}_{ct} < L_{ct-1}$, i.e. $F_c \times (\frac{\bar{L}_{ct}}{L_{ct-1}} - 1)^2$. Though the labor laws do not explicitly protect non-regular labor, non-regular workers who lose their jobs can complain to the courts, and the ruling of courts varies greatly across states and over time. The uncertainty endemic in this environment contributes to the firing cost of non-regular workers as explained in Section 2.2. Since non-regular workers receive less protection from the law, the firing cost F_c is expected to be lower than that of regular workers. We assume firing cost are as follows.

$$F_c = \bar{F}_c + c_{Fc}L_{c,t-1} \tag{7}$$

The actual realized employment is subject to an employment shock which captures, for example, workers leaving for personal reasons. We assume that the targeted employment level of firms is the median realized employment. The log actual employment is assumed to follow a log normal distributions with a mean of $log(\bar{L}_{ct})$ and $log(\bar{L}_{rt})$ and standard deviations $\sigma^{\varepsilon}_{Lc}$ and $\sigma^{\varepsilon}_{Lr}$.

$$logL_{rt} \sim \mathcal{N}(log(\bar{L}_{rt}), \sigma^{\varepsilon}_{Lr}) \tag{8}$$

$$logL_{ct} \sim \mathcal{N}(log(\bar{L}_{ct}), \sigma^{\varepsilon}_{Lc}) \tag{9}$$

5.3.2 Capital Adjustment and its Costs

As with labor adjustment, we assume convex capital adjustment costs. If the targeted capital level is less than the last periods, i.e., $\bar{K}_t < K_{t-1}$, the adjustment costs are $F_K \times (\frac{\bar{K}_t}{K_{t-1}} - 1)^2$, and if $\bar{K}_t > K_{t-1}$, adjustment costs are $H_K \times (\frac{\bar{K}_t}{K_{t-1}} - 1)^2$ where

$$H_K = \bar{H}_K + c_{HK}K_{t-1} \tag{10}$$

$$F_K = \bar{F}_K + c_{FK}K_{t-1} \tag{11}$$

As with labor, we assume that the actual realized capital is subject to an investment shock. We assume that the targeted capital level of firms is the median realized capital. The log actual capital is assumed to follow a log normal distributions with a mean of $log(\bar{K}_{ct})$ and $log(\bar{K}_{rt})$ and standard deviations σ^{ε}_K and σ^{ε}_K.

$$logK_t \sim \mathcal{N}(log(\bar{K}_t), \sigma^{\varepsilon}_K) \tag{12}$$

5.3.3 Exit, Dormancy, Production and their costs

In each period, a firm must choose among three options: exit, dormancy and production. When firms choose to exit, firms are assumed to get the scrap value of the firm, f^E. A low

f^E means exit is costly. When firms exit, firms sell their capital which become available to others. We assume that f^E follows a log normal distribution to capture idiosyncratic shocks.

$$f^E \sim log\mathcal{N}(\mu_f^E, \sigma_E^2) \tag{13}$$

For example, it may unexpectedly get a large offer for its brand name or it gets lucky and the court moves quickly in its favor, both of which would reduce the realized value of its exit costs. We need these shocks so as to better match the data as similar looking firms may behave differently with respect to exit in terms of their choices.

When firms choose to produce, they pay a fixed cost f^P irrespective of the size of output. This cost follows a log normal distribution $log\mathcal{N}(\mu_f^P, \sigma_P^2)$. When firms choose dormancy, they need not pay this fixed cost, but they still need to pay their employed regular and non-regular workers, as well as the per period rental price of capital.

During dormancy and production, firms adjust their employment subject to the specified convex adjustment costs. Dormancy has two roles. First, firms are able to adjust their labor employment during dormancy to avoid the large firing cost of laying off all their workers. Second, staying in dormancy has an option value for firms that receive a large negative shock, but have hopes that this is temporary. Such firms may choose dormancy over exit. [30]

5.3.4   Entry and its Costs

In each period, a mass of firms M^e pay an entry cost F^e to enter the market. After a firm enters the market, it decides what to do based on the realization of its initial productivity, $\tilde{\phi}_0$. Firms realize their initial productivity only after deciding to enter. Knowing their productivity, they decide what level of capital and labor (regular and non-regular) to target taking into account the adjustment costs that need to be paid. Then, the actual input levels

---

[30]In the data, the transition from dormant without workers to active is about 3 percent. Firms that are dormant without workers for three years are dropped from the data and such firms are going to be even worse than those dormant without workers for no more than three years. Hence, the probability of their becoming active after being dropped will be even lower than 3 percent.

are realized. With all this information in hand, the firm decides whether to produce or be dormant. Then we move into the next period. This is depicted in the timeline in Figure 7.

Firms enter till the expected profits from doing so are zero. We assume that the stock of capital in the economy is fixed at $\bar{K}$. Thus, both the mass of entrants M^e and p_K are endogenous. A larger number of entrants increases the demand for capital and thus pushes up the cost of acquiring capital, p_K. In equilibrium, this price p_K is such that the demand for capital equals the total stock of capital in the market. The mass of firms that enter is pinned down by ex-ante profits being zero.
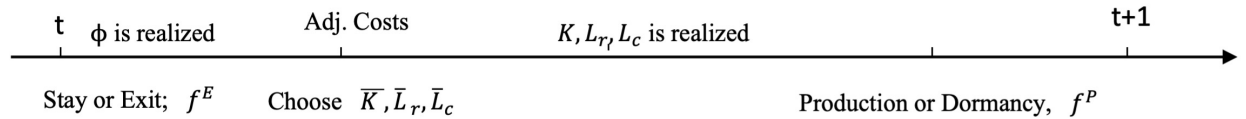

Figure 7: Timeline of Firms' Choices

5.4   Value function of Firms

Next, we describe the value functions of firms, as well as their policy functions. Let s_t be the state of the firm: $s_t = (\tilde{\phi}_t, L_{ct-1}, L_{rt-1}, K_{t-1})$. We describe the value function for any period $t \geq 1$ and then by backward induction, we derive the value function at period $t = 0$.

For period $t \geq 1$

For any period $t \geq 1$, the value function of a firm is denoted by V. As usual, the value function is the maximum of what it obtains if the firm stays or exits. If it exits, it obtains its scrap value as well as the value of its capital, less the adjustment costs associated with reducing its labor (regular and non-regular) as well as its capital to zero. We define its value if it chooses to stay to be $V^S(s_t)$.

$$V(s_t) = \mathbb{E}_{\{f^E\}} \left\{ \max_{d=E,S} \{ f^E + p_K K_t - F_r - F_c - F_K, V^S(s_t) \} \right\} \tag{14}$$

The value of staying in the market is,

$$
\begin{aligned}
V^S(s_t) &= \max_{\bar{L}_{ct}, \bar{L}_{rt}, \bar{K}} \Bigg\{ \mathbb{E}_{\{L_{ct}, L_{rt}, K_t\}} \Big[R(\tilde{\phi}_t, L_{ct}, L_{rt}, K_t) - w_c L_{ct} - w_r L_{rt} + \delta^V \mathbb{E}_{\tilde{\phi}_{ft+1}|\tilde{\phi}_{ft}} V(s_{t+1}) \Big] \\
&\quad - H_c \times \left(\frac{\bar{L}_{ct}}{L_{ct-1}} - 1 \right)^2 \times \mathbb{1}\{\bar{L}_{ct} \geq L_{ct-1}\} - F_c \times \left(\frac{L_{ct-1}}{\bar{L}_{ct}} - 1 \right)^2 \times \mathbb{1}\{\bar{L}_{ct} < L_{ct-1}\} \\
&\quad - H_r \times \left(\frac{\bar{L}_{rt}}{L_{rt-1}} - 1 \right)^2 \times \mathbb{1}\{\bar{L}_{rt} \geq L_{rt-1}\} - F_r \times \left(\frac{\bar{L}_{rt}}{L_{rt-1}} - 1 \right)^2 \times \mathbb{1}\{\bar{L}_{rt} < L_{rt-1}\} \\
&\quad - H_K \times \left(\frac{\bar{K}_t}{K_{t-1}} - 1 \right)^2 \times \mathbb{1}\{\bar{K}_t \geq K_{t-1}\} - F_K \times \left(\frac{\bar{K}_t}{K_{t-1}} - 1 \right)^2 \times \mathbb{1}\{\bar{K}_t < K_{t-1}\} \Bigg\}
\end{aligned}
$$

The firm is choosing its targeted levels of factors denoted by $\bar{L}_{rt}, \bar{L}_{ct}, \bar{K}_t$. As there is some randomness in what the actual levels end up being, it integrates over this randomness. It chooses whether to produce or be dormant once the actual levels are realized. $R(\cdot)$ is the expected value-added net of fixed production cost (with the expectation being over only the fixed costs).[31]

$$
R(\tilde{\phi}_t, L_{ct}, L_{rt}, K_t) = \mathbb{E}_{\{f^P\}} \max_{P,D} \{ VA(\tilde{\phi}_t, L_{ct}, L_{rt}, K_t) - f^P, 0 \}
$$

For period $t = 0$

Firms pay the entry cost F^e before their productivity is realized. We assume that the initial productivity $\tilde{\phi}_0$ is drawn from a initial log normal distribution with a mean $\frac{\tilde{\gamma}_0}{1-\tilde{\gamma}_1}$ and a variance $\frac{(\sigma_\gamma^\varepsilon)^2}{1-\tilde{\gamma}_1^2}$. In period 0, the value function of a firm is V_0 is

$$
V_0(\tilde{\phi}_0) = \max_{d=E,S} \left\{ 0, \max_{L_r, L_c, K, f^P} \{ VA(\tilde{\phi}_0, L_c, L_r, K) - f^P - p_K \times K + \delta^V \mathbb{E}_{\tilde{\phi}_1|\tilde{\phi}_0} V(s_1) \} \right\}
$$

Firms choose stay in the market $(d = S)$ when the value of entering is greater than zero, otherwise firms exit the market immediately. We assume zero ex-ante profits and free entry.

---

[31]The value-added is defined in Eq (2).

Therefore, the expected payoff of entry equals to the entry cost.

$$F^e = \int_{\tilde{\phi}_0} V_0(\tilde{\phi}_0) dG_0(\tilde{\phi}_0)$$

6 Identification and Estimation

6.1 Identification

The full set of model parameters includes the discount factor δ^V, the capital depreciation factor δ^K, demand elasticity σ, per period factor prices w_c, w_r, the price of acquiring capital, p_K, the input share in production, α_L, α_I, α_K, α_{Lc} and α_{Lr}, labor adjustment costs $\bar{H}_c, c_{Hc}$, $\bar{F}_c, c_{Fc}, \bar{H}_r, c_{Hr}, \bar{F}_r^L, c_{Fr}^L, \bar{F}_r^S, c_{Fr}^S$, Labor and capital shocks σ_K^ε, σ_{Lr}^ε, σ_{Lc}^ε, production and exit costs μ_f^P, σ_P^2, μ_f^E, σ_E^2, productivity evolution $\tilde{\gamma}_0$, $\tilde{\gamma}_1$, $\tilde{\sigma}_\gamma^\varepsilon$. Our strategy is to calibrate certain parameters and estimate the remaining. The parameters we calibrate are δ^V, δ^K, α_I and σ. The rest of the parameters, i.e.,

$$\theta = \{\tilde{\gamma}_0, \tilde{\gamma}_1, \tilde{\sigma}_\gamma^\varepsilon, \alpha_L, \alpha_K, \alpha_{Lc}, \bar{H}_c, c_{Hc}, \bar{F}_c, c_{Fc}, \bar{H}_r, c_{Hr}, \bar{F}_r^L, c_{Fr}^L, \bar{F}_r^S, c_{Fr}^S, \sigma_{Lc}^\varepsilon, \sigma_{Lr}^\varepsilon, \sigma_K^\varepsilon, \mu_f^P, \sigma_P, \mu_f^E, \sigma_E\}$$

are estimated using the dynamic model.

We now discuss the intuition behind the identification. The key parameters in this paper are the means and variances of the fixed production cost (μ_f^P, σ_P^2) and the scrap value (μ_f^E, σ_E^2). Recall that fixed costs need to be paid if production is to occur and dormancy is a way of avoiding them and that scrap value is obtained upon exit. The probability of production and probability of dormancy given productivity and labor employment identifies these parameters. Ceteris paribus, a lower probability of production indicates a higher mean fixed costs (μ_f^P), while a higher probability of dormancy indicates a higher mean exiting cost (i.e. lower scrap value μ_f^E). For a given mean production shock, an increase in its variance (σ_P^2) will move mass toward the tails and thereby reduce the probability of

production. Similarly, for a given mean scrap value, an increase in its variance (σ_E^2) will raise the probability of exit as this occurs when the scrap value is large enough.

The hiring and firing costs are, as is usual, identified through the transition of employment over states. A small increase in employment in response to a positive productivity shock implies a larger hiring cost, and a small decrease with a negative productivity shock implies a larger firing cost. Greater variance in employment, conditional on the state, s_t, indicates larger deviations from firms' targeted employment levels, i.e., larger employment shocks (σ_{Lc}^ε, σ_{Lr}^ε). Similarly, the transition of capital over time identifies the capital adjustment costs and capital shocks. The mean and transition matrix of productivity $\tilde{\phi}_{ft}$ help identify the process of productivity evolution $\tilde{\gamma}_0$, $\tilde{\gamma}_1$, $\sigma_\gamma^\varepsilon$. Once θ is estimated, we solve out the entry cost F^e such that firms have zero expected profits by entering the market.

6.2 Estimation Procedure

In this Sub-section we use Figure 8 to help lay out how the approach of Golombek and Raknerud (2018), which we base our estimation on, works for these unfamiliar with it. Golombek and Raknerud (2018) uses indirect inference. Simple versions of indirect inference familiar in trade are simulated method of moments where we choose moments that help pin down parameters in the model. One might use a simple moment, like a mean or variance, or a more complex one like a regression. One would then run the regression on the data (the auxiliary model), choose parameters, generate data, and run the same regression on the generated data. The object would be to choose parameters to make the two estimated regression lines as close as possible. This is laid out in the first and second column.

However, it is very computationally intensive to follow this brute force approach as it involves solving the dynamic model many, many, times in order to generate the data. Moreover, in our setting there is an additional complication: firms face discrete (active, dormant, exit) and continuous choices (how much labor and capital to employ). Small changes in the fixed costs of production and in entry costs could result in discrete changes in the simulated

Usual Indirect Inference	Quasi-Likelihood	Our Approach

Step 1
Estimate Auxiliary Model using actual data

Auxiliary Model
$y = \phi x + \varepsilon$

Estimate: $\hat{\phi}_{data}$

Specify the Quasi-LLH function of the Aux Model.
Estimate: $\hat{\phi}_{data}$

Estimate: $\hat{\phi}_{data}$

Step 2
• Guess parameters of the structural model
• Simulate Data
• Est. Aux model using simulated data

• Guess: θ
• Simulate data under θ^{guess}
• Estimate: $\hat{\phi}_{sim} = \phi(\theta)$

Estimating the quasi-LLH function is computationally demanding

By definition:
Slope of Q-LLH=0 at $\hat{\phi}_{data}$

Use simulated data to re-evaluate slope of Q-LLH at $\hat{\phi}_{data}$

Step 3
Iterate step 2 until estimated Aux. model parameters are similar w/ actual & simulated data

• Iterate Step 2, until we find $\hat{\theta}$, such that:
$\hat{\phi}_{data} = \phi(\hat{\theta})$

Iterations are extremely slow

Iterate Step 2, until we find $\hat{\theta}$, such that slope of Q-LLH at $\hat{\phi}_{data} \approx 0$
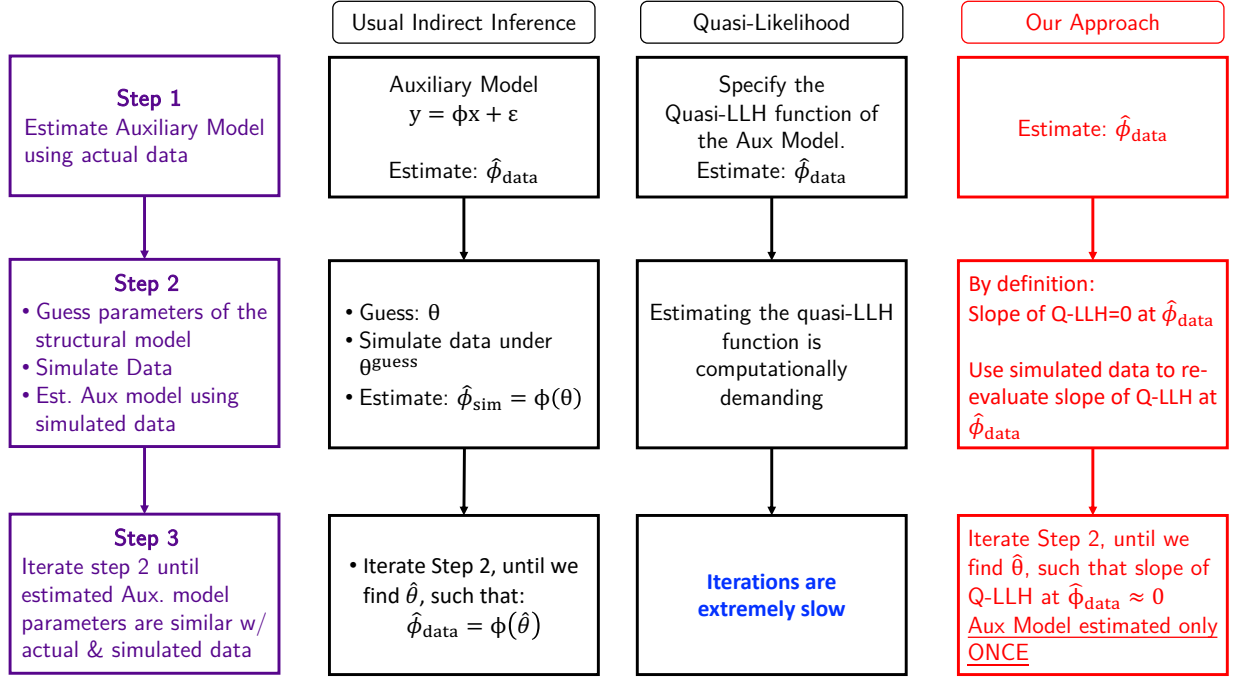Aux Model estimated only ONCE

Figure 8: The Procedure of Indirect Inference

data. This would make using the brute force approach above even more difficult and would create problems in using gradient-based methods.

To deal with this issue, Golombek and Raknerud (2018) casts the problem in terms of the probability of being active, dormant and exiting, which allows the use of gradient methods. They use a quasi-likelihood (QL) approach. They take the likelihood function as the auxiliary model (think of this as analogous to the regression run on the data) and choose the parameters of the auxiliary model to maximize the QL. Call these parameters $\hat{\theta}^a_{Data}$. Next, choose some particular values of the structural parameters to be estimated, θ. Generate data from the model conditional on these parameters. Finally, treat this data as if it was the true data and maximize the quasi-likelihood function to obtain another estimate of the auxiliary model $\hat{\theta}^a_{SimData}$. The object is to make $\hat{\theta}^a_{SimData}$ as close to $\hat{\theta}^a_{Data}$ as possible. This is laid out in the third column.

Moreover, to reduce the computational burden they do not evaluate the entire LF, only

the derivative at parameters estimated for the actual data. [32] This is laid out in the last column. The auxiliary model we use consists of different likelihood functions for different subsets of the structural parameters as outlined below.

Before we proceed, we need to deal with one problem with the ASI data, namely that the data is missing for some periods, and this is more so for small firms.[33] To deal with such gaps in the data, we adapt the simulation procedure to mimic missing patterns in the real data. Define the status of a firm, z_{it}, to have four potential values, E for never reappearing in the data later, D for dormancy, P for production, and M for missing from the data but reappearing in the data later. Define $p_{missing}(L_{c,it-1}, L_{r,it-1}, K_{r,t-1})$ to be the probability of missing a data point at t, conditional on the employment and capital stock, that is, it is the probability that $z_{it} = M$.[34] We first use the actual data to estimate the function $p_{missing}$, and then incorporate $p_{missing}$ into the simulation process. Thus, the simulated data now also has holes in the data due to it being missing that follow the same pattern as in the data.

6.3 Preliminary Results

Here we show some preliminary estimates (without standard errors as these need to be bootstrapped) using data on firms in good states, in sectors where the labor intensity is above the median. Our estimates should be thought of more as a "proof of concept", i.e., proof that our approach works and seems to give reasonable estimates.

We need to get values of the parameters, including those associated with the production function, the discount factor, and the depreciation of capital as well as an estimate of the wages of contract and non-contract workers. These we calibrate as in Table 3. We calibrate the numbers for the share of intermediate inputs and for wages from the data as a simple

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[32] If this derivative is not zero, the parameters are adjusted to bring this derivative as close to zero as possible by minimizing the square of the difference in the derivatives.

[33] The data can be missing either because the firm was not sampled in the period. Recall that firms with less than 100 workers are only sampled according to the sampling frame. Hence, this is likely for smaller firms. The data could also be missing because though the firm was sampled, it did not comply.

[34] This can be made as flexible as desired. For example, it can be made conditional on the number of years of dormancy in the past, or another variable that might matter.

average across firms in our data. We estimate the coefficients of capital, regular workers, and other workers in the production function in the estimation of the value added function.[35]

Table 3 gives the values of the calibrated parameters. We take the discount factor and the depreciation factor to be the same and .9. σ takes 3.94 as it is calculated based on the median markup estimated in De Loecker et al. (2016). The share of intermediate inputs, α_I, is calculated based on the simple average of expenditure share of materials by firms in the ASI data.

Table 3: Calibrated Parameters

Parameters		Parameters	
δ^V	0.9	α_I	0.57
δ^K	0.9	w_r (1,000 rupees)	50
σ	3.94	w_c (1,000 rupees)	117

The average annual wage of all workers in the period of the data, whether regular or not is about 50,000 rupees a year. The wage of no-regular workers is higher than that of regular workers because this includes contract workers and managers. [36]

We also need to estimate the parameters associated with the evolution of productivity, the fixed cost of production, factor adjustment costs, and scrap value, as well as α_K (which give us α_L as the sum of α_K, α_L and α_I equals unity) and the coefficient of regular workers in the production of labor services, (recall $\alpha_L r$ ($\alpha_L c = 1\text{-}\alpha_L r$). Table 4 gives these estimates. We restrict our attention to good states and labor-intensive sectors as a test run of our approach. We are most interested in the adjustment costs for regular labor for large and small firms which the setting suggests should be larger for large firms and in the scrap value which again we expect to be small, and perhaps even negative.

First, note that there is a fair degree of persistence in productivity as the slope of the

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[35]We group contract workers with managers as many firms do not employ contract workers and both are not covered by the IDA.

[36]Contract workers make 37,000 rupees on average in good states and 34,000 in bad states. This is what the firms pay for them so that the worker would get even less given the agency supplying contract workers would take a cut. This suggests contract workers are different (less skilled) compared to regular workers. Managers make Rs. 165,000 in good states and 141,000 in bad states.

evolution of productivity is .86. Moreover, scrap value is indeed negative on average though there is considerable variance in its realization as the mean and standard deviation are of roughly the same size (718.65 and 785.72 respectively.) The firing costs for regular workers in large firms are higher than that for small firms as expected, as both the intercept and slope of the function that defines the convexity of these costs are higher (68.73 and 10.73 for large firms, versus 45.36 and 3.76 for small firms.) This is in line with expectations as the restrictions on firing only cover large firms.

Comparing the firing costs across regular and non-regular workers we see that both the slope and intercept of the relevant function defining the extent of firing costs for non-regular (contract workers and managers) are lower than that for regular workers in large firms in good states. This is in line with expectations as contract workers are not subject to the IDA provisions. Next we use the model to better understand the role of policy-induced adjustment costs in explaining the lack of, especially labor-intensive, manufacturing in the Indian economy.

Table 4: Parameter Estimates

Panel 1: Production Function and Profitability Process		Panel 5: Adjustment Costs	
γ_0	0.19	Capital	
γ_1	0.86	$\bar{H}_K$	28.62
$\sigma_\gamma^\varepsilon$	0.94	c_{HK}	9.21
α_K	0.23	$\bar{F}_K$	331.89
$\alpha_L r$	0.67	c_{FK}	4.2
Panel 2: Fixed Production Cost		Regular Workers	
μ_f^P	-10.55	$\bar{H}_r$	15.48
σ_P^2	9.8	c_{Hr}	22.36
Panel 3: Scrap Value		$\bar{F}_r^L$	68.73
μ_f^e	-718.68	c_{Fr}^L	10.73
σ_e^2	785.72	$\bar{F}_r^S$	45.36
Panel 4: Shocks to Factor Employment		c_{Fr}^S	3.76
σ_K^ε	0.56	Non-regular Workers	
σ_{Lr}^ε	0.86	$\bar{H}_c$	-3.41
σ_{Lc}^ε	0.95	c_{Hc}	6.82
		$\bar{F}_c$	30.33
		c_{Fc}	16

7 Counterfactual Exercises

We will focus on good states and labor-intensive sectors only.

7.1 Varying Scrap Value: Good States, Labor Intensive Sectors

We would like to better understand how changing the scrap value affects exit rates. To do so, we perform the following exercise. We raise scrap value and note that doing so raises the exit rate. Since the exit rate is easier to comprehend and compare across time and space, we choose to plot outcomes as a function of the exit rate generated by the exit costs, rather than the exit costs themselves. We then see how exit rates relate to variables of interest like value-added, average productivity, employment, and the mass of firms. This is depicted in Panel (a) of Figure 9. Since we are doing this counterfactual for good states, all these curves hit zero when we consider their value at the simulated exit rate in good states given our estimates. The average exit rate generated by the model is low, around 8 percent in good states.[37]

We draw three vertical lines at the exit rates in the labor intensive sector in good states, bad states, and overall in the US. The first thing to note is that value-added and employment follow roughly the same path. If the exit rate in good states was that of the US, both would rise by about 37% while the mass of firms would rise by about 65%. Thus, much of the action is coming from entry. However, average productivity (weighted by value-added share) falls by about 20%. This comes from entry becoming less selective as exit costs fall and exit becomes easier. As a result, entering firms are less productive. An increase in scrap value also raises the average productivity of exiters. Entry becoming less selective reduces average productivity while the increase in the productivity of exiters raises it as depicted in Panel (c). If the former dominates, we would see average productivity fall (as we do) as the exit rate rises. Panel (b) shows that the mean years spent in dormancy and the mean age of

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[37]Recall that we are measuring exit as exiting the data, (as a firm that is dormant for 3 years is dropped from the data) so our exit rates will tend to be higher than those coming using the approach based on firm registration or used by Hsieh and Klenow (2014).

firms fall as exit costs fall (the exit rate rises). Panel (d) shows how the price index falls as the exit rate rises.

(a) VA, Productivity, Emp. and Firm Mass

(b) Length of Dormancy and Age

(c) Productivity of Entrants and Exiters
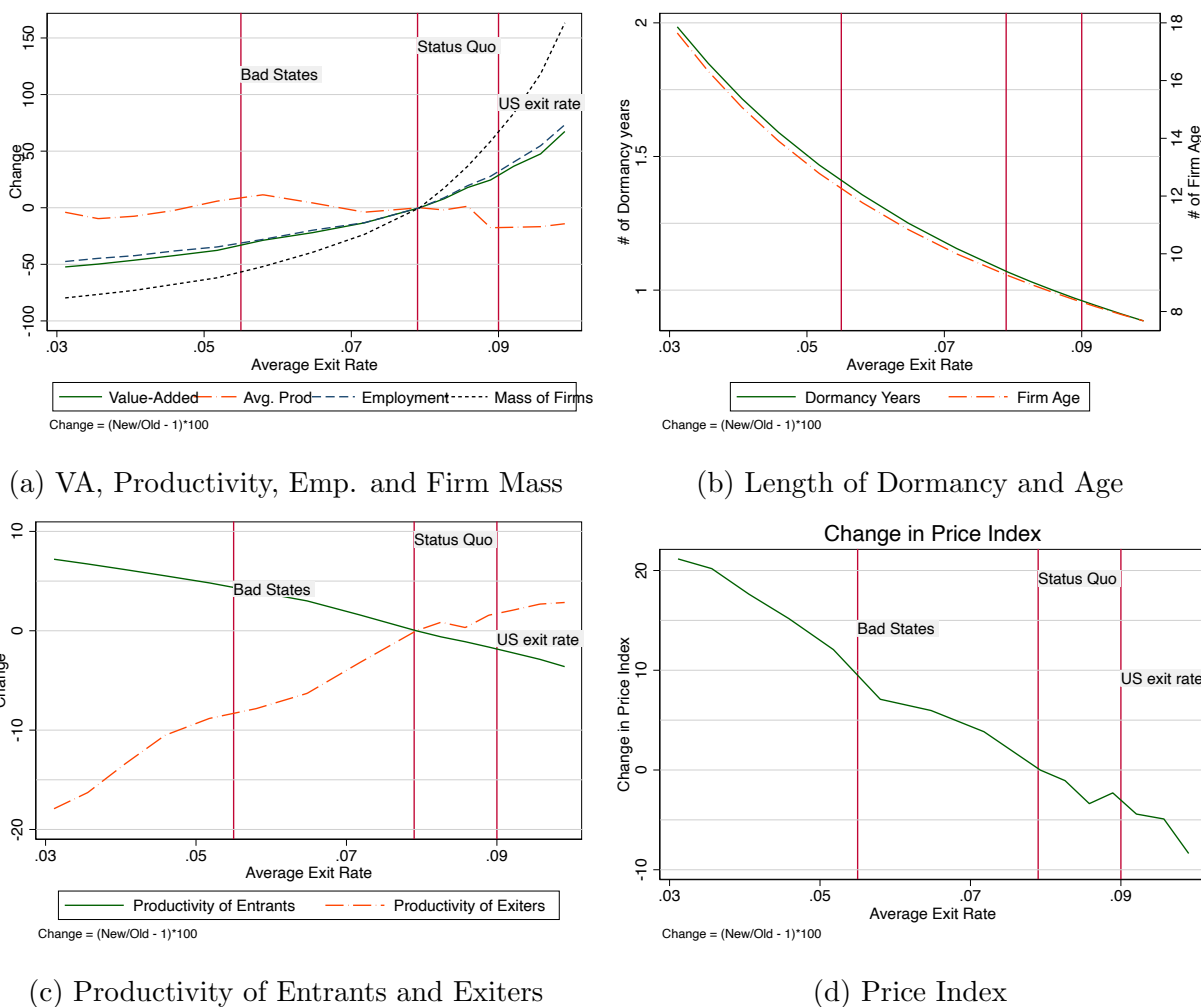

(d) Price Index

Figure 9: Counterfactual Exercises for Good States and Labor Intensive sectors with an Increase in the Scrape Value

So far we have made a very conservative assumption: namely that the overall supply of capital is fixed. We chose to do this both to be conservative and because part of what comes under capital is land used in manufacturing. The land market is also subject to considerable friction, see Sood (2020). Table 5 provides some idea of how sensitive our results are to this assumption. A back-of-the-envelope calculation of how welfare changes can be made by looking at the effect on indirect Utility which with homothetic preferences boils down to the effect on real income, i.e., the change in value-added divided by price. These results are to

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be found in the bottom row of Table 5.[38] As the elasticity of the supply of capital rises going

from 0 to .5, we see that the effect rise quite considerably by a factor roughly between 2 and

3.

Table 5: Sensitivity to Capital Supply Elasticity: Scrap Value

	ε_K			
Changes in	0	0.1	0.2	0.5
Value-added	37.13%	46.1%	56.3%	91.2%
Employment of Workers	39%	61.8%	73.0%	111.6%
Mass of Firm	65.3%	96.1%	110%	156.5%
Price Index	-3.5%	-6.6%	-9.9%	-14.8%
Welfare	7.21%	9.38%	11.68%	19.38%

Note: Manufacture share in GDP is 16.5% in 2004 (The World Bank); Consumption share of manufacturing goods is 24.7% in 2004 (The WIOD).

7.2 Varying Firing Costs: Good States, Labor Intensive Sectors

We perform an analogous exercise here to that in the previous sub-section. We reduce the

coefficient on the percentage change in labor when labor is let go (which reduces the convexity

of the adjustment costs associated with firing workers and reduces exit rates) till we get the

desired exit rate. Recall that firms that want to exit will have to lay off any workers they

have so firing costs are a part of exit costs and reducing them raises exit rates.[39] We then

see how these exit rates relate to variables of interest like value-added, average productivity,

employment, and the mass of firms. This is depicted in Panel (a) of Figure 10. All these

curves hit zero when we consider their value at the simulated exit rate of 8 percent. As in

Figure 9, we draw three vertical lines at the exit rates for labor-intensive sectors in good

states, bad states, and overall in the US.

The first thing to note is that for firing costs that induced the US exit rate, value-added

increases by 72 percent (versus 37 percent had this exit rate been induced via increases in

---

[38]For example, With a manufacturing share of 16.5% in GDP, an increase of 37% in value added in manufacturing (assuming all of manufacturing was similarly affected) and a fall in the price index of 3.5%, and a consumption share of manufactured goods of 24.7% we get a welfare change of 7.21% when the supply elasticity is zero.

[39]In other words, we again choose to plot outcomes as a function of the exit rate generated by the exit costs, rather than the exit costs themselves.

scrap value.) However, while employment in Figure 9 tracked value-added, in Figure 10 employment is essentially unchanged (it rises by only 0.8 percent) had the US entry rate been induced. This suggests that reductions in firing costs are more efficacious in raising value-added, while increases in scrap value are better at raising employment. The mass of firms would rise by about 142.7 percent versus 65.3 percent when scrap value increases are used to attain the US exit rate. Thus again, much of the action is coming from the intensive margin of entry. Moreover, (value added weighted) average productivity rises by about 20 percent (instead of falling by roughly this): though entry becomes less selective so young firms are less productive, exit becomes easier which raises the average productivity of old firms. The former reduces average productivity while the latter raises it and the latter dominates as young firms tend to be small which results in their being given lower weight in productivity which is a weighted average with weights given by their value-added share. Panel (c) shows that indeed, the simple average of the productivity of exiters rises. This increase is much larger (about 120 percent) as is the fall in the productivity of entrants (about 150 percent) compared to Figure 9.

Panel (b) shows that the mean years spent in dormancy by firms falls slightly (by .08 years) while the average age of firms falls by about .8 years as the exit rate rises to the US level. This is similar to what happens in Figure 9. Panel (d) shows the price index falls by about 15 percent if the US exit rate is induced compared to 3.5 percent in Figure 9, consistent with the steep rise in productivity, and consequent fall in prices.

Table 6 follows Table 5 to consider the sensitivity of the results for reducing firing costs to the elasticity of capital supply. The sensitivity of all but employment is about a third less in table 6, compared to Table 5. However, interestingly, the response of employment is huge. In Table 5, the increase in employment went from 39% to 111.6% as the elasticity of capital supply went from 0 to .5. In Table 6 it goes from .8% to 32.2%. This suggests that there are huge synergies in terms of employment creation between capital and labor when we think of policies that reduce labor market firing costs.

A feature worth pointing out when we compare Table 5 and Table 6 in the baseline scenario, is that raising scrap value seems to target employment, while reducing labor adjustment costs seems to target value added. Raising scrap value to attain the US exit rate gives an employment increase of 39% and a value-added increase of 37.13% in our baseline scenario where capital is fixed. Using reductions in labor adjustment costs to achieve the US exit rate gives an employment increase of only .8% but a value-added increase of 72.4%. This indicates that, in the baseline scenario at least, reducing labor adjustment costs to attain the US exit rate is good for raising value added. This makes sense as firms will fire unproductive workers who use intermediate inputs but add little or no value. This will raise the value added of firms that choose to stay. Firms that choose to exit make little or negative value-added anyway and as they find it easier to leave, value added will if anything rise. In addition, the mass of firms will rise, raising value added. However, all of this need not be good for employment: firms that choose not to exit will shed unwanted workers, and as decreasing firing cost also reduces exit costs, more firms will choose to exit and this will also reduce employment. Countering this is the fact that the mass of firms rises which raises employment.
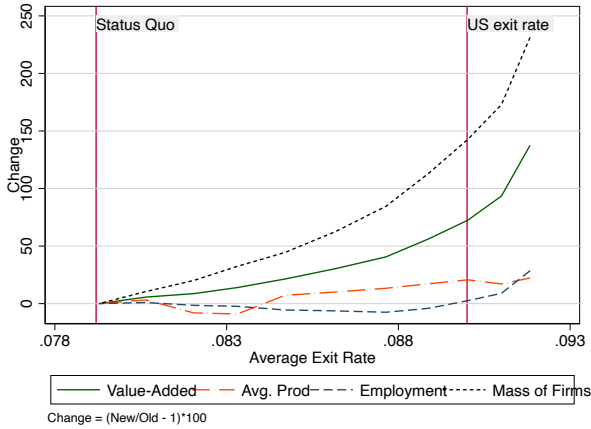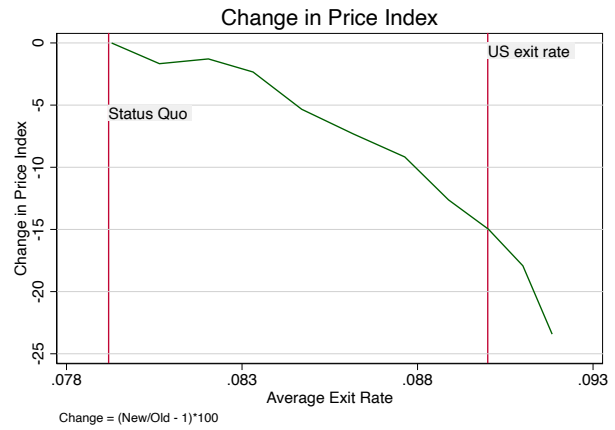
(a) VA, Productivity, Emp. and Firm Mass
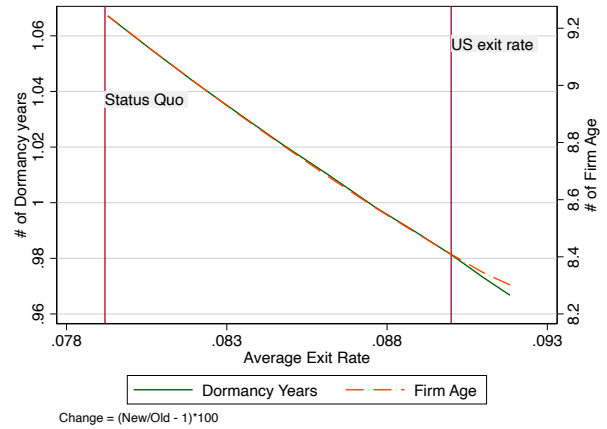
(b) Length of Dormancy and Age
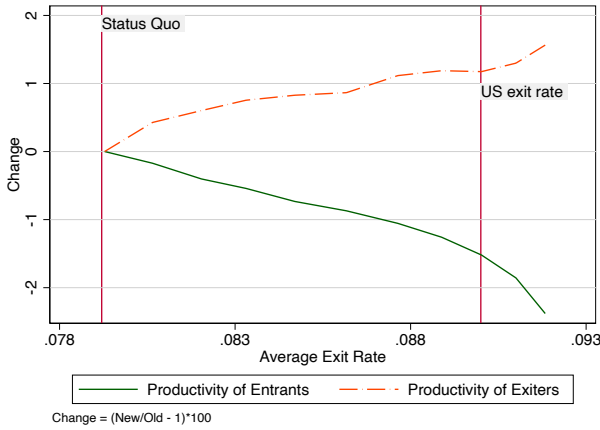
(c) Productivity of Entrants and Exiters

(d) Price Index

Figure 10: Counterfactual Exercises for Good States and Labor Intensive sectors with a Reduction in the Labor Firing Cost

Table 6: Sensitivity to capital supply elasticity with Reduction of Labor Firing Cost

	ε_K			
Changes in	0	0.1	0.2	0.5
Value-added	72.4%	84.3%	97.8%	141.4%
Employment of Workers	0.8%	1.0%	8.1%	32.2%
Mass of Firm	142.7%	159.6%	177.5%	239.5%
Price Index	-15.3%	-17.9%	-20.4%	-24.6%
Welfare	16.20%	18.90%	22.0%	31.1%

Note: Manufacture share in GDP is 16.5% in 2004 (The World Bank); Consumption share of manufacturing goods is 24.7% in 2004 (The WIOD).

8 Conclusion

Exit costs are relevant for all economies, developed and developing. They are manifested primarily as bankruptcy costs in developed countries like the U.S. and tend to be manifested in additional ways in developing ones. Indian policymakers, in particular, have been concerned about exit barriers. The Government of India's annual Economic Survey in 2015-16 stated that *"India has made great strides in removing the barriers to the entry of firms, talent, and technology into the Indian economy. Less progress has been made in relation to exit. Thus, over the course of six decades, the Indian economy moved from 'socialism with limited entry to "marketism" without exit."*

Policymakers however have little to go on in terms of identifying the extent and variation across sectors and regions in the extent of exit barriers. Our research is designed to identify and quantify exactly this and aiding governments in formulating the right policies. However, this paper is only the first step in this regard.

Future work would include extending the model to a general equilibrium setting with multiple aggregate sectors (e.g. Hopenhayn 1992) and including a spatial dimension (e.g. Caliendo and Parro 2015). The former would allow for feedback from greater employment in manufacturing to demand in all sectors and potentially magnify the impact of reducing adjustment costs. A spatial dimension would provide a better understanding of the location decisions of firms and labor as well as allow the study of spillovers across Indian states. Particular features that would be important in a full-blown quantitative exercise are allowing for internal transport costs (Redding and Rossi-Hansberg 2017), endogenizing the location choice of firms (Basile 2008; Fajgelbaum, Morales, Suárez Serrato, and Zidar 2019; Head and Mayer 2014), and migration decisions (Bryan, Chowdhury, and Mobarak 2014; Desai and Chatterjee 2016; Keshri and Bhagat 2012; Monte, Redding, and Rossi-Hansberg 2018; Rai 2018; Redding and Rossi-Hansberg 2017).

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A Empirical Facts

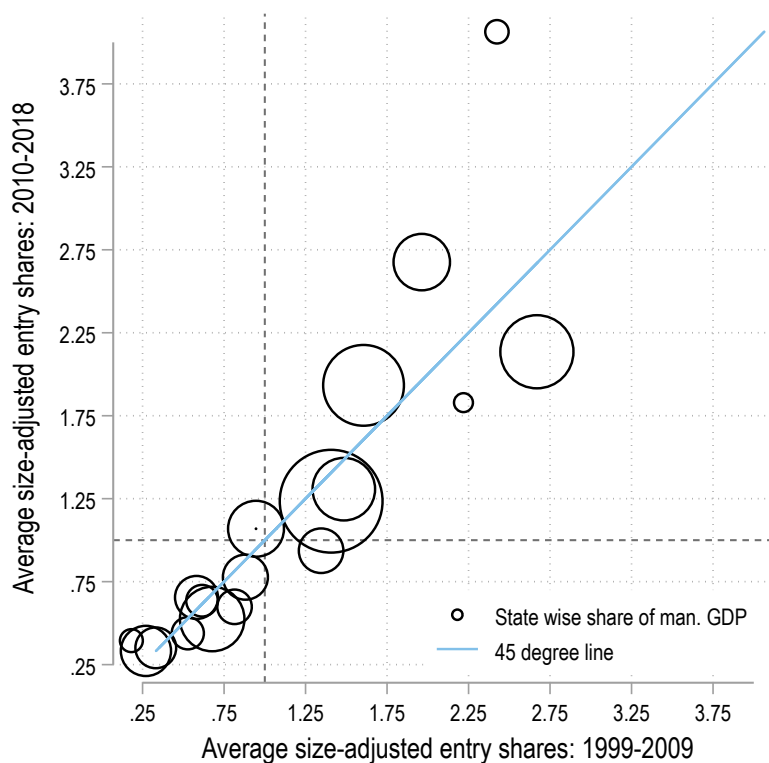## A.1 Persistence of Entry Shares Over Time

Figure 11: Persistence of size-adjusted entry shares over time

Notes: Size-adjusted entry share of state s at time t: entry share of state s at time t normalized by its population share. The above figure plots the relationship between size-adjusted entry shares averaged from 1999-2009 and size-adjusted entry shares averaged from 2010-2018. Each circle represents a state; size of the circle is determined by state-wise share of overall manufacturing GDP.

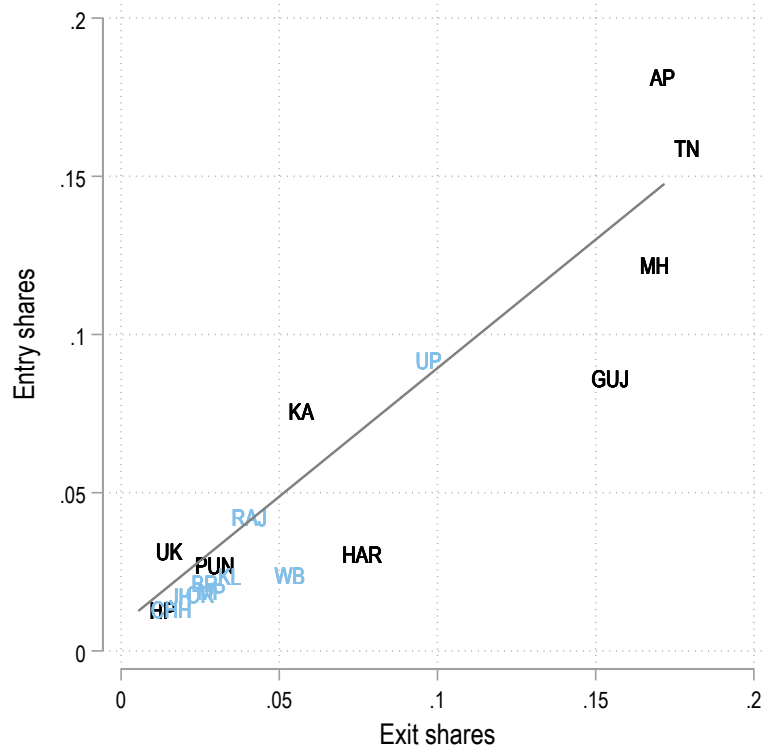## A.2 Entry Shares versus Exit Shares

Figure 12: State-wise entry versus exit shares

Notes: This figure plots the relationship between un-adjusted entry and exit shares across states. The correlation between the two is 0.93.
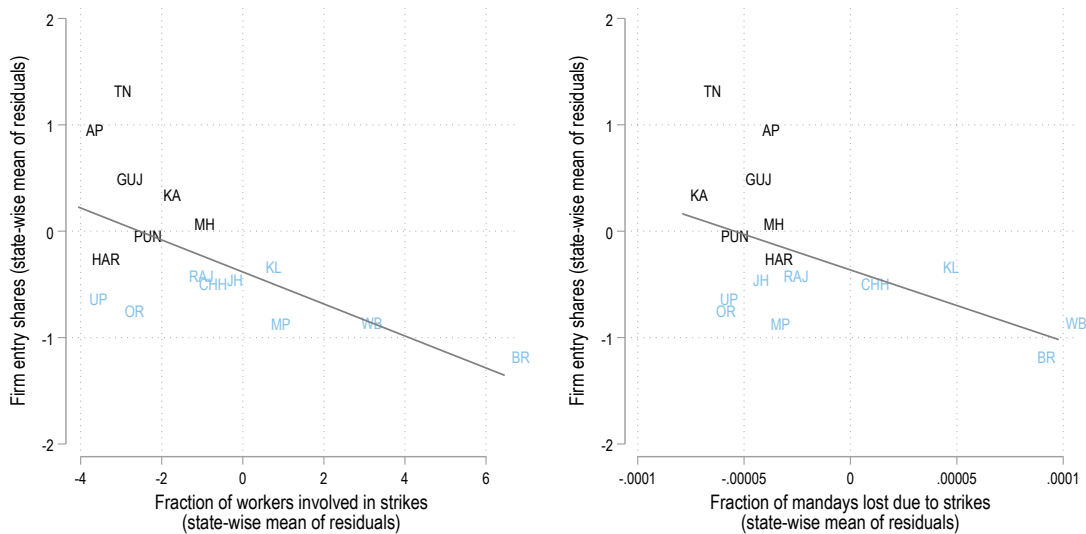
A.3 Entry Shares versus Labor Unrest

Figure 13: Entry Shares vs Labor Unrest

Notes: Each observation is at the state-year level. We use 'fraction of workers involved in strikes' and 'fraction of man-days lost due to strikes' as our measures of labor unrest. The above figures plot the OLS relationship between size-adjusted entry shares and size-adjusted measures of labor unrest after controlling for: (1) year fixed-effects that account for aggregate shocks, (2) share of regular workers since only regular workers have the right to strike, and (3) share of man-days contributed by regular workers. The figures show that a 1 standard deviation (s.d.) higher fraction of workers participating in strikes across states or a 1 s.d. higher fraction of man-days lost due to strikes is associated with 0.62 s.d. and 0.53 s.d. lower entry shares respectively. The figures also clearly show that good states as a group have lower labor unrest and higher entry and the opposite is true for bad states. Data on fraction of workers involved in strikes and man-days lost due to strikes is from the CMIE 'States of India' database.

A.4   Transition to Dormancy
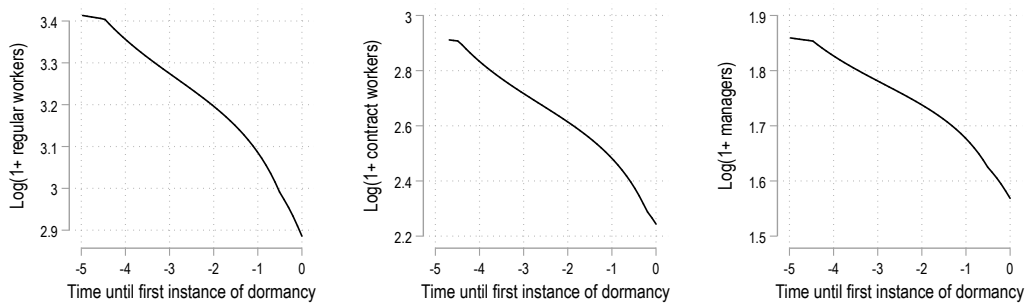
(a) Regular (left panel), contract (middle panel), and managerial (right panel) employment
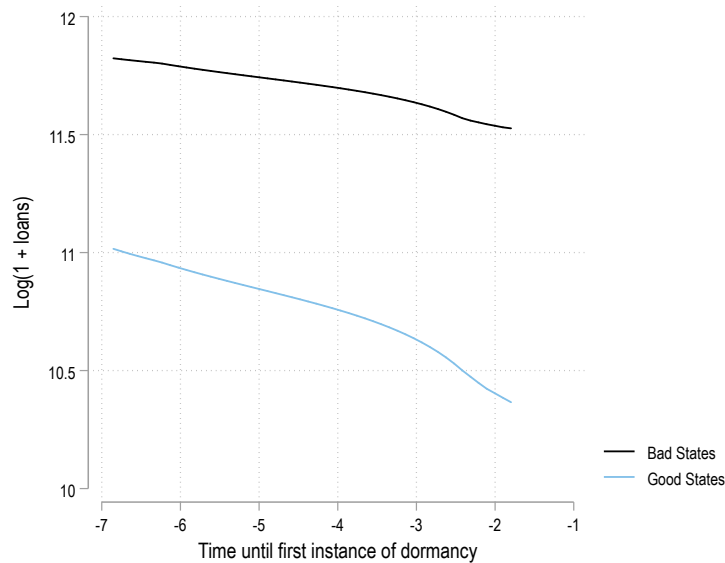
(b) Plant loans

Figure 14: Plant employment and loans as they transition to dormancy

Notes: To plot these figures, we first residualize the y-variable and x-variable of plant fixed effects. Second, we re-scale the residuals by adding back the unconditional sample means of the respective variables. Third, we divide observations into 20 equally sized bins based on their x values and calculate the mean of y and x values within each bin. The solid lines above are a polynomial fit of the resulting mean values.

A.5 Using inflation to incentivize attrition

Table A1: Nominal wage per worker of regular workers: high-inflation versus low-inflation years

	(1)	(2)	(3)
	log(wage per regular worker)	log(wage per regular worker)	log(wage per regular worker)
Linear time trend	-0.0111*	-0.0181***	-0.0238***
	(0.00500)	(0.00511)	(0.00506)
Quadratic time trend	0.00427***	0.00495***	0.00530***
	(0.000274)	(0.000273)	(0.000274)
1{High_inflation} = 1	-0.00693	0.00989	0.0212
	(0.0112)	(0.0113)	(0.0147)
t=-1		-0.108***	-0.134***
		(0.0256)	(0.0302)
t=-2,-3		0.00677	0.0192
		(0.0189)	(0.0220)
t=-4,-5,-6		0.00759	0.0200
		(0.0133)	(0.0165)
High_inflation*t=-1			0.0727
			(0.0439)
High_inflation*t=-2,-3			-0.0370
			(0.0259)
High_inflation*t=-4,-5,-6			-0.0294
			(0.0189)
Constant	10.03***	10.07***	10.09***
	(0.0650)	(0.0633)	(0.0629)
N	17682	17682	17682
Plant FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A2: Nominal wage per worker of contract workers: high-inflation versus low-inflation years

	(1)	(2)	(3)
	log(wage per contract worker)	log(wage per contract worker)	log(wage per contract worker)
Linear time trend	0.00120	-0.00389	-0.00213
	(0.0129)	(0.0153)	(0.0152)
Quadratic time trend	0.00390***	0.00483***	0.00494***
	(0.000604)	(0.000637)	(0.000649)
$1\{\text{High\_inflation}\} = 1$	-0.0527*	-0.0412	-0.0713*
	(0.0253)	(0.0267)	(0.0313)
$t=-1$		-0.244**	-0.296***
		(0.0756)	(0.0885)
$t=-2,-3$		-0.0454	-0.0915
		(0.0542)	(0.0601)
$t=-4,-5,-6$		-0.00685	-0.00731
		(0.0344)	(0.0420)
$\text{High}_i nflation * t = -1$			0.0692
			(0.129)
$\text{High}_i nflation * t = -2, -3$			0.0936
			(0.0633)
$\text{High}_i nflation * t = -4, -5, -6$			-0.0290
			(0.0422)
Constant	9.954***	10.01***	10.01***
	(0.171)	(0.171)	(0.174)
N	5453	5453	5453
Plant FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

B Estimation Procedure

Part 1: $\theta_1 = \left\{ \tilde{\gamma}_0, \tilde{\gamma}_1, \sigma_\gamma^\varepsilon, \alpha_L, \alpha_K, \alpha_{Lc}, \alpha_{Lr} \right\}$

Under the assumption that $L_{i,ct}, L_{i,rt}, K_{i,t}$ is strictly exogenous, we obtain a simple log-likelihood function of θ_1^a given $(L_{i,c}, L_{i,r}, K_i, VA_i)$. In order to track the evolution of firm productivity, we need to use information on firms that produced in the previous period as well as this period. This explains the need for the indicator function. Taking past and current capital and labor choices and past value added as exogenous, we construct the likelihood that the value added today takes the value observed in the data. This assumption of exogeneity is clearly not true as it is inconsistent with the structural model. Nevertheless, there is nothing
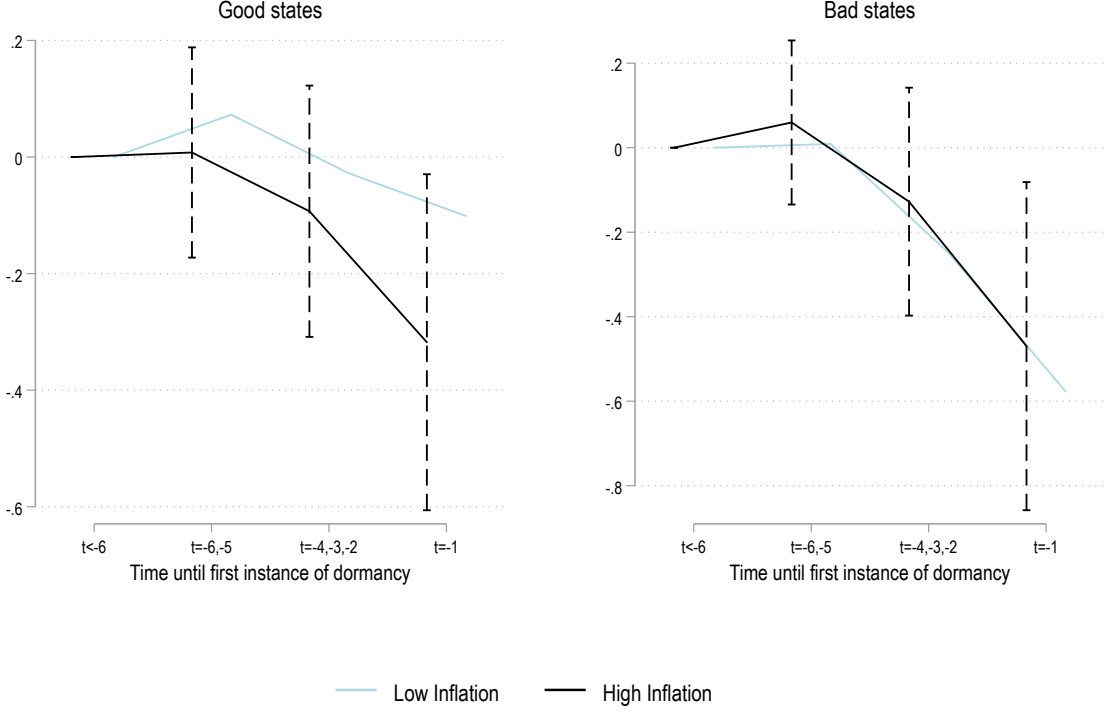
Figure 15: Adjustment of Contract Workers and Inflation: Good vs Bad States

to stop us from using this as the log likelihood function of our chosen auxiliary model.

$$\ln l_1(\theta_1^a; L_{i,c}, L_{i,r}, K_i, \ln VA_i) = \sum_{t=1}^{T} \mathbb{1}\{z_{it} = P; z_{it-1} = P\} \ln f_{\theta_1^a}(\ln VA_{it}|L_{i,ct}, L_{i,rt}, K_{i,t}, \ln VA_{it-1}, L_{i,ct-1}, L_{i,r}$$

where, $f_{\theta_1^a}(\ln VA_{it}|\cdot)$ is the density of normal distribution implied by Eq (2) and Eq (3).
Thus, $\hat{\theta}_1^a$ maximizes the following objective function given data Y_{Data}.

$$\ln L_1(\theta_1^a; Y_{Data}) = \sum_i \ln l^1(\theta_1^a; L_{i,c}, L_{i,r}, K_i, VA_i) \qquad (16)$$

Part 2: $\theta_2 = \{\mu_f^P, \sigma_P\}$

Recall that the choice of producing versus dormancy comes down to whether value added from production exceeds the fixed costs of operating. This follows from the fact the choice of whether to produce or not is made after choosing employment and capital and once the
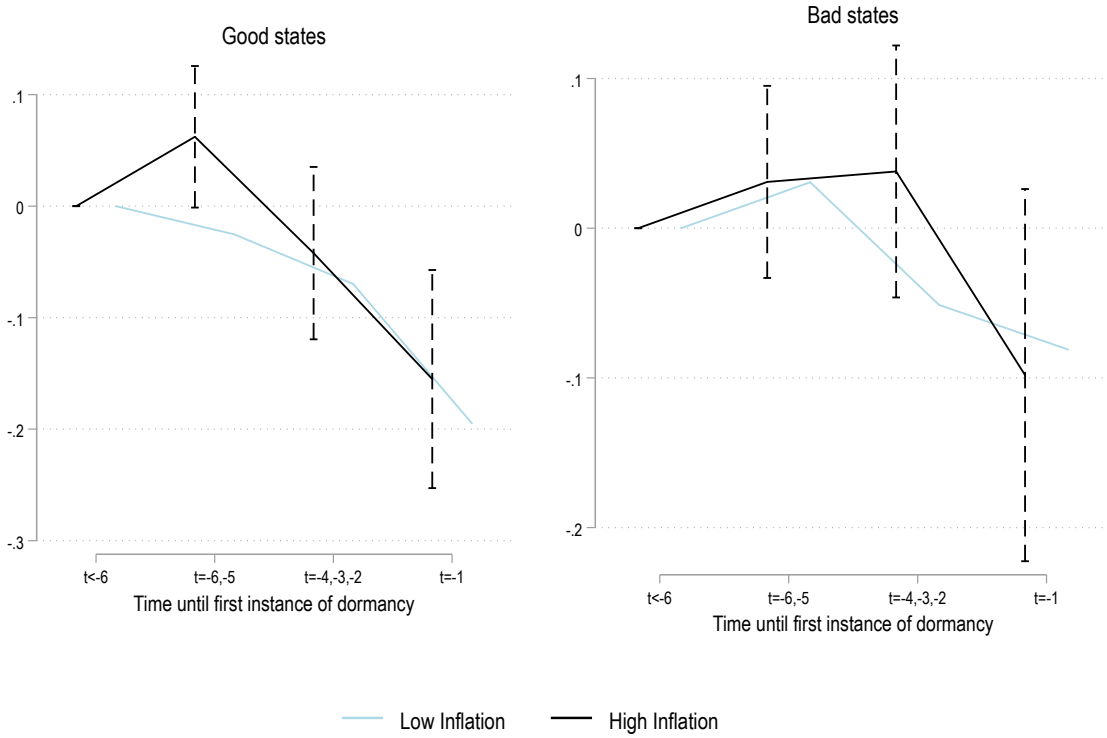
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Figure 16: Adjustment of Managers and Inflation: Good vs Bad States

shock to fixed costs is realized. Consequently, payments to labor and capital need to be made independent of whether the firm produces or is dormant. Given the estimated parameters in $\hat{\theta}_1^a$, we can construct our approximation of $\tilde{\phi}_{it}$ defined as $\hat{\tilde{\phi}}_{it} = \frac{VA_{it}}{L_{i,t}^{\alpha_L} K_{i,t}^{\alpha_K}}$. This is based upon our definition of productivity in Eq (2) The log-likelihood function of θ_2 is constructed based on firms production vs dormancy choices.

$$\ln l_2(\theta_2^a; \tilde{\phi}_{it}, L_{i,ct}, L_{i,rt}, K_{it}, \hat{\theta}_1^a) = \ln Prob\{VA(\tilde{\phi}_{it}, L_{i,ct}, L_{i,rt}, K_{it}) - f^P > 0\} \qquad (17)$$

Thus, $\hat{\theta}_2^a$ maximizes the following objective function given data Y_{Data} and $\hat{\theta}_1^a$.

$$\ln L_2(\theta_2^a; Y_{Data}, \hat{\theta}_1^a) = \sum_{i,t} \ln l_2(\theta_2^a; \tilde{\phi}_{it}, L_{i,ct}, L_{i,rt}, K_{it}, \hat{\theta}_1^a) \qquad (18)$$

Part 3: $\theta_3 = \{\bar{H}_K, c_{HK}, \bar{F}_K, c_{FK}, \bar{H}_r, c_{Hr}, \bar{F}_r^B, \bar{F}_r^S, c_{Fr}, \bar{H}_c, c_{Hc}, \bar{F}_c, c_{Fc}, \sigma_{Lc}^\varepsilon, \sigma_{Lr}^\varepsilon, \sigma_K^\varepsilon, \mu_f^E, \sigma_E^2\}$

$\bar{H}_K, c_{HK}, \bar{F}_K, c_{FK}, \bar{H}_r, c_{Hr}, \bar{F}_r^B, \bar{F}_r^S, c_{Fr}, \bar{H}_c, c_{Hc}, \bar{F}_c, c_{Fc}$ are the adjustment costs defined in Eq (4), Eq (5), Eq (6), Eq (7), Eq (10) and Eq (11). The parameters $\sigma_{Lc}^\varepsilon, \sigma_{Lr}^\varepsilon, \sigma_K^\varepsilon$ denote the variances of the shocks to employment and capital: recall, the firm chose its targeted levels but the actual levels were random as defined in Eq (8), Eq (9) and Eq (12). μ_f^E, σ_E^2 are the mean and variance of the distribution of scrap value as defined in Eq (13).

In the third step of the specification of the auxiliary model, we construct a partial quasi-likelihood estimate of θ_3^a based on the joint decisions made by the firm regarding labor, capital adjustment, and exit. As before, we need to use data on firms that produced in the previous period. This accounts for the indicator variable's presence below.

The likelihood component for a particular firm is given by

$$\ln l_3(\theta_3^a; \hat{\theta}_1^a, \hat{\theta}_2^a, Y_{Data}) = \sum_{t=1}^{T} \mathbb{1}\{z_{it-1} = P\} \ln g_{(\theta_3^a; \hat{\theta}_1^a, \hat{\theta}_2^a)}(L_{i,ct}, L_{i,rt}, K_{i,t}, z_{i,t} | \hat{\bar{\phi}}_{it}, L_{i,ct-1}, L_{i,rt-1}, K_{i,t-1}) \quad (19)$$

where, $g_{(\theta_3^a, \hat{\theta}_1^a, \hat{\theta}_2^a)}(\cdot)$ can be expressed as

$$g_{(\theta_3^a; \hat{\theta}_1^a, \hat{\theta}_2^a)}(L_{i,ct}, L_{i,rt}, K_{i,t}, z_{i,t} | \hat{\bar{\phi}}_{it}, L_{i,ct-1}, L_{i,rt-1}, K_{i,t-1}) =$$

$$g_{(\theta_3^a, \hat{\theta}_1^a, \hat{\theta}_2^a)}(L_{i,ct}, L_{i,rt}, K_{i,t} | z_{i,t}, \hat{\phi}_{i,t}, L_{i,ct-1}, L_{i,rt-1}, K_{i,t-1}) \times p_{(\theta_3^a, \hat{\theta}_1^a, \hat{\theta}_2^a)}(z_{i,t} | \hat{\phi}_{i,t}, L_{i,ct-1}, L_{i,rt-1}, K_{i,t-1}).$$

The first function gives the likelihood that we see the labor and capital values present in the data and the second function gives the likelihood that we see the particular choice in z_{it} made by the firm. The likelihood that a firm is producing in the data is the probability it chooses P (independent of whether it is in the data or not) times the probability it is in the data. The argument for D being chosen in the data is analogous. The probability that the firm is missing is the probability it is producing but missing plus the probability it is dormant but missing. We know it has not exited as it shows up later in the data. Finally, We say that z_{it} takes the value exit if it is not in the data from here on. Hence, the probability that z_{it}

takes the value exit is made up of the probability that the firm is producing or dormant but missing in the data plus the probability that it actually exited.

$$p_{(\theta_3^a,\hat\theta_1^a,\hat\theta_2^a)}(z_{i,t} = P|s_{i,t}) = Prob\{z_{it} = P|s_{it}\} \times (1 - p_{missing}(L_{i,ct-1}, L_{i,rt-1}, K_{i,t-1}))$$

$$p_{(\theta_3^a,\hat\theta_1^a,\hat\theta_2^a)}(z_{it} = D|s_{i,t}) = Prob\{z_{i,t} = D|s_{it}\} \times (1 - p_{missing}(L_{i,ct-1}, L_{i,rt-1}, K_{i,t-1}))$$

$$p_{(\theta_3^a,\hat\theta_1^a,\hat\theta_2^a)}(z_{it} = M|s_{i,t}) = (Prob\{z_{i,t} = P|s_{it}\} + Prob\{z_{i,t} = D|s_{it}\}) \times p_{missing}(L_{i,ct-1}, L_{i,rt-1}, K_{i,t-1})$$

$$p_{(\theta_3^a,\hat\theta_1^a,\hat\theta_2^a)}(z_{it} = E|s_{i,t}) = (Prob\{z_{i,t} = P|s_{it}\} + Prob\{z_{i,t} = D|s_{it}\}) \times p_{missing}(L_{i,ct-1}, L_{i,rt-1}, K_{i,t-1})$$

$$+ Prob\{z_{i,t} = E|s_{it}\}$$

When $z_{i,t} = P$, we are able to observe $s_{i,t}$. Let $h_c(\cdot)$, $h_r(\cdot)$, $h_K(\cdot)$ be the policy function of the structural model. That is, the optimal employment and capital choices are

$$\bar{L}_{i,ct} = h_c(s_{i,t}) \quad \bar{L}_{i,rt} = h_r(s_{it}) \quad \bar{K}_{i,t} = h_K(s_{it})$$

Therefore,

$$g_{(\theta_3^a,\hat\theta_1^a,\hat\theta_2^a)}(L_{c,it}, L_{r,it}, K_{i,t}|z_{i,t}, s_{i,t}) = f_c(L_{c,it}|h_c(s_{i,t}), \sigma_{Lc}^\varepsilon) \cdot f_r(L_{r,it}|h_r(s_{i,t}), \sigma_{Lr}^\varepsilon) \cdot f_K(K_{i,t}|h_K(s_{i,t}), \sigma_K^\varepsilon)$$

where, $f_c(\cdot)$ is the pdf of a log normal distribution with mean $h_c(\cdot)$ and standard deviation σ_c^ε as defined in Eq (9). $f_r(\cdot)$ and $f_K(\cdot)$ are defined analogously.

In sum, we can write $g_{(\theta_3^a,\hat\theta_1^a,\hat\theta_2^a)}(\cdot)$ as the following.

$$g_{(\theta_3^a,\hat\theta_1^a,\hat\theta_2^a)}(L_{i,ct}, L_{i,rt}, K_{i,t}, z_{i,t}|\hat{\hat\phi}_{it}, s_{i,t})$$

$$= \begin{cases} g_{(\theta_3^a,\hat\theta_1^a,\hat\theta_2^a)}(L_{c,it}, L_{r,it}, K_{i,t}|z_{i,t} = P, s_{i,t}) \cdot p_{(\theta_3^a,\hat\theta_1^a,\hat\theta_2^a)}(z_{i,t} = P|s_{i,t}) \\ p_{(\theta_3^a,\hat\theta_1^a,\hat\theta_2^a)}(z_{i,t}|s_{i,t}) \quad \text{if } z_{i,t} = D, M, E \end{cases}$$

Adding the likelihood components of each firm as defined in Eq (19) gives the likelihood

function as follows

$$\ln L_3(\theta_3^a; \hat{\theta}_1^a, \hat{\theta}_3^a), Y_{Data}) = \sum_i \ln l_3(\theta_3^a; \hat{\theta}_1^a, \hat{\theta}_2^a, Y_{Data}) \tag{20}$$

We obtain the partial quasi-likelihood estimator of θ_3^a by maximizing Eq (20) with respect to θ_3^a. This optimization problem is computationally demanding as it requires reevaluation of the value function for each trial value θ_3^a, which means that the functional fixed-point has to be solved each time a trial value is tested.

Indirect inference

The partial quasi-likelihood estimator $\hat{\theta}^a = (\hat{\theta}_1^a, \hat{\theta}_2^a, \hat{\theta}_3^a)$ satisfies a score moment condition. To see this, define

$$l(\theta^a|Y_{Data}) = l^1(\theta_1^a|Y_{Data}) + l^2(\theta_2^a|\theta_1^a, Y_{Data}) + l^3(\theta_3^a|\theta_1^a, \theta_2^a, Y_{Data})$$
$$\frac{\partial l(\Theta^a|Y_{Data})}{\partial \theta^a} = \left[\frac{\partial l^1(\theta_1^a|Y_{Data})'}{\partial \theta_1^a}, \frac{\partial l^2(\theta_2^a|\theta_1^a, Y_{Data})'}{\partial \theta_2^a}, \frac{\partial l^3(\theta_3^a|\theta_2^a, \theta_2^a, Y_{Data})'}{\partial \theta_3^a} \right]'$$

Then $\hat{\Theta}^a$ satisfies the score condition

$$\frac{1}{N} \sum_i^N \frac{\partial l(\theta^a|Y_{Data})}{\partial \theta^a} = 0$$

We then simulate S trajectories for each of the N firms, i.e., SN trajectories in total. Let $Y_{Sim}(\theta)$ denote an arbitrary simulated trajectory for firm i for a given θ.

$$\hat{\theta} = \left\| \arg\min_\theta \sum_i^N \sum_{s=1}^S \frac{\partial l(\hat{\theta}^a|Y_{Sim}^{(s)}(\theta))}{\partial \theta^a} \right\|$$

Since we have discrete choices in the model, the simulated trajectories are discontinuous in the parameters. Golombek and Raknerud (2018) provides a way to smooth the objective function. The basic idea is to replace the simulated discrete choice $z_{it}^{(s)}(\theta)$ with its conditional

expectation given the simulated state variables $\hat{z}_{it}^{(s)}(\theta)$. That is, $\hat{z}_{it}^{(s)}(\Theta)$ is a conditional survival probability.

Next, we explain how to calculate the smoothed trajectories $Y_{Sim}^{*(s)}$, and we choose $\hat{\Theta}$ such that

$$\hat{\theta} = \left\| \arg\min_{\theta} \sum_{i}^{N} \sum_{s=1}^{S} \frac{\partial l(\hat{\theta}^a | Y_{Sim}^{(s)}(\theta))}{\partial \theta^a} \right\|$$