No Country for Dying Firms: Evidence from India*

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Abstract

This paper identifies exit barriers as a new reason for India's underdeveloped manufacturing sector. These barriers not only deter entry but also trap resources in unproductive firms. We document that Indian institutions generate such barriers and provide causal evidence of their effects. Using a dynamic model that separately identifies direct exit barriers from labor and capital adjustment costs, we find that exit barriers are quantitatively significant, particularly in low-performing states and labor-intensive industries. Our analysis yields three findings. First, reducing firing costs raises value added but reduces employment, whereas relaxing direct exit barriers increases both. Second, simultaneous reform of labor firing costs and direct exit barriers yields synergies. Third, sequencing matters: addressing direct exit barriers before labor firing costs preserves employment while improving efficiency. Finally, we show that exit subsidies are more effective at raising value added, while entry subsidies are more effective at increasing employment.

Keywords: Exit barriers, aggregate productivity, firm dynamics, misallocation, India, economic development.

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1 Introduction

Schumpeterian creative destruction, the process in which innovative production units replace outdated ones, propels the economy toward the technological frontier. Structural impediments to this dynamic process can severely hinder productivity growth and economic development. Specifically, barriers to exit, such as bankruptcy and factor adjustment costs, can stifle firm creation and dampen economic dynamism. In this paper, we leverage microdata from Indian manufacturing plants to investigate the critical role of such exit barriers in shaping India's economic development.

Understanding the aggregate impact of exit barriers is crucial for informed policy-making and development economics. These impediments manifest in various forms, from stringent size-based labor regulations that raise the cost of firing workers (as in India and France) to compulsory contributions to unemployment insurance that can rise when workers are let go (as in the U.S.) and protracted, costly bankruptcy proceedings (as in India). Regulations that raise exit costs reduce expected profits and thereby act as entry costs, deterring potential entrants. In addition, resources are misallocated as inefficient firms remain, tying up assets that could be used more productively elsewhere. Hence, while high exit barriers and firing costs aim to preserve employment, they can do the opposite, resulting in lower labor demand, employment, and wages if the adverse effects on entry outweigh the benefits of preserved employment.

Although our empirical context is India, these economic mechanisms have broad relevance. For example, they are central to current debates about the diverging economic trajectories of the US and European economies, particularly since the Covid-19 pandemic.[1] It has been argued that part of the reason for this disparity could lie in the different pandemic responses. Europe's strategy focused on preserving jobs and firms through work sharing. Workers at firms that reduced hours were compensated for their earnings loss, which inadvertently caused economic rigidity. In contrast, while unconditionally subsidizing firms that claim to have suffered due to the pandemic, the US also opted to provide direct payments to laid-off individuals. This gave workers a safety net that let them search for a better job match and allowed the labor market to adjust. This difference may have enabled greater economic flexibility and resilience in the US and contributed to its dynamism post-COVID.

We study India's manufacturing sector for three reasons. First, India is now one of the world's largest and fastest-growing countries, but several puzzles related to India's macro-development and structural transformation do not have a coherent explanation. These include India's premature de-industrialization (Rodrik, 2016), the existence of a long tail of unproductive firms (Hsieh and Klenow, 2014), and under-performance in key low-skill manufacturing sectors (Chatterjee and Subramanian, 2023). Our paper can shed light on all three of these. As we argue below, manufacturing has more exit barriers for institutional reasons.[2] As exit barriers are entry barriers,

[1] The US has done well through 2024 relative to the G7 economies in economic growth, driven by robust innovation, productivity, and job creation. On the U.S. vs. Europe debate, see The Economist, The Financial Times, and this Economic Letter from the Federal Reserve Bank of San Francisco.

[2] The Industrial Disputes Act (IDA) applies to manufacturing, plantations, and mines and makes firing workers

manufacturing, especially labor-intensive manufacturing, becomes less attractive. This helps explain the first and third facts above. Exit barriers will also induce firms that want to exit to remain, which explains the second fact.

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

Third, there is prima facie evidence that exit costs in India are high. Manufacturing in India has one of the lowest firm exit rates in the world (see Figure 1a below).[3] The Industrial Disputes Act (IDA) makes it hard to fire workers for large plants (100 or more workers in the past and now 300 or more workers in some states) and covers Manufacturing, Mining, and Plantations. Exit rates in sectors that are not specifically covered by the IDA are roughly twice as high (see Figure 1b).[4] Many firms in India remain dormant (produce nothing, with or without workers) for a long time before they finally exit.[5] 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.[6]

Even if a firm is not involved in any litigation or disputes (and litigation is likely given the lack of a clear path to bankruptcy until recently) and has all the necessary documentation in order, the process of voluntary closure still takes approximately 4.3 years. Of this, about 2.8 years are dedicated solely to securing clearances and refunds from various government departments, such as the Income Tax, Provident Fund, and Goods and Services Tax authorities. In comparison, voluntary liquidation processes are significantly shorter in other countries: about 12 months in Singapore, 12-24 months in Germany, and 15 months in the United Kingdom (Economic Survey of India 2020-21).

Our analysis has two parts. First, we provide both suggestive and causal evidence that exit barriers are very present and impose significant costs on firms in India. They reduce entry, misallocate resources, and create a long right tail in the age distribution of firms. These data

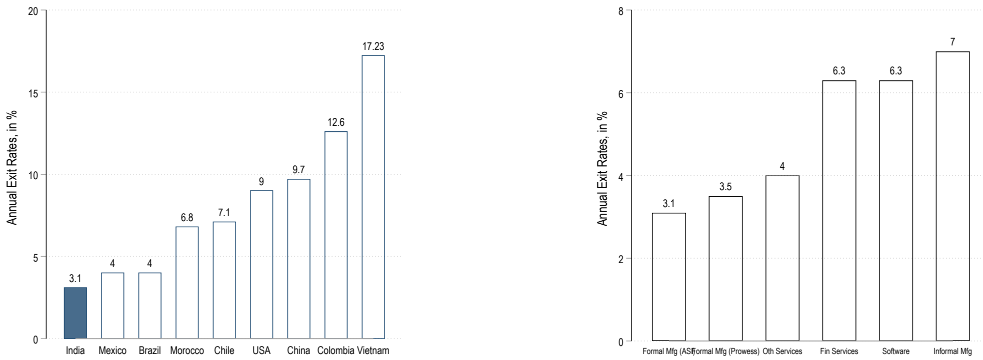
(which would be needed to exit) very difficult, especially for large firms.

[3]While no direct exit measure is available in the ASI data, we follow Hsieh and Klenow (2014) to measure exit rates. They proposed comparing the mass of plants from a specific vintage (i.e., the initial year of production) from ASI survey rounds, e.g., in years t and $t + \Delta$. Since the sample is representative, the only reason the survey in year $t + \Delta$ would have a lower mass of plants of a specific vintage compared to year t is because of the exit of some plants. By aggregating across vintages, we can estimate plant exit rates between years t and $t + \Delta$. For more details on the calculation, please see section B.1 in the Appendix.

[4]Exit rates are also much lower in formal manufacturing than in informal manufacturing, as shown in Figure B.5 in the Online Appendix.

[5]20% of all registered companies in India are dormant [Link]. Dormancy rates in the Annual Survey of Industries (ASI) data that we use in this paper are lower than in the national registry of companies maintained by the Ministry of Corporate Affairs (MCA). In the ASI data, around 4-5 percent of firms are dormant with workers, and another 4-5 percent are dormant without workers. There are two main reasons for this difference. First, the MCA data includes all registered companies, including non-manufacturing companies. Second, the ASI data drops dormant firms without workers after three consecutive years.

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



(a) Exit Rates in the Manufacturing Sector

(b) Annual Exit Rates by Sector in India

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 et al. (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 et al. (2022) for 2006; China - calculated from Annual Surveys of Industrial Production for 2006; Vietnam - calculated from Vietnam enterprise census for 2007. Panel (b): Exit rates of service sector firms have been computed from the Prowess database. Other services include accommodation & food services, transport & storage services, and administrative & support services. The annual exit rate of informal manufacturing plants has been computed from NSS data for 1994-95 and 2015-16. For more details on exit calculations, please see section B.1 in the Appendix.

patterns are novel and a contribution in themselves. In addition, we classify Indian states as high- or low-performance based on their entry shares. See Section 4 for more details.

Second, we build and estimate a dynamic model of firm behavior in the presence of exit costs. This framework allows us to see how exit barriers can interact with each other and how reducing them individually can have adverse effects, which can be avoided by doing so jointly. For instance, we show that reducing labor firing costs alone raises value added but reduces employment, a politically costly outcome, while reducing firing costs and bankruptcy costs raises both. Exit barriers could be institutional, like those coming from labor regulations. They could be observed or unobserved, like variations in the implementation of similar policies or idiosyncrasies in judicial outcomes across states. Our approach captures both. In particular, we allow for flexible functional forms to estimate labor and capital adjustment costs, and, in addition, 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.[7]

Our estimated parameters suggest that firing regular workers is 2.7-5.4 times as costly as firing contract workers. This is consistent with the fact that regular workers, unlike contract workers, are protected by labor laws in India. Firing costs for regular workers are greater in low-performance states, amounting to as much as 284% of the average annual wages in these states. We find that exit costs, other than labor and capital adjustment costs, are high as well. In high and low-performance

[7]Our model is challenging to estimate as firms make both discrete (exit, produce, dormant) and continuous (factor adjustment) choices, unlike most models on firm dynamics. We build on the estimation strategy proposed by Golombek and Raknerud (2018) and use the smoothing properties of the conditional expectations operator to overcome this challenge.

states, these amount to 79% and 140%, respectively, of the annual sales of the average firm in these states.

Next, we use the estimated model to conduct policy counterfactuals. In particular, we change policy so that exit rates in India are as high as 50% of the U.S. exit rates. We have two policy instruments to achieve this: (1) lowering firing costs that mimic labor reforms, or (2) increasing the scrap value of firms that mimic institutional reforms like improving judicial performance. We find that both policies increase aggregate value added and mass of firms by 14-19%. The average duration of dormancy falls from 3.46 to 2.37 years. Since reducing exit costs raises the value of entering, new firms with slightly lower productivity enter the market. As a result, the net effect on average productivity is a modest 3.23-3.85%.

The effect on employment, however, is very different under the two policies. Lowering exit costs (i.e., increasing the scrap value) increases employment by about 8%; reducing firing costs, on the other hand, reduces employment by 14%. The negative effect is partly driven by the elasticity of capital supply. Hence, the first policy takeaway is that reducing firing costs can be detrimental to employment if capital markets are rigid or over-regulated. In such settings, labor laws might actually serve a purpose.

We also find that there are strong synergies between the two policy instruments. The net effects of implementing both policies together are greater than the sum of the parts. Taken together with the results on employment, this suggests that reducing red tape related to exit and other factors captured by the scrap value should be done before relaxing labor regulations, such that the adverse effects on employment are mitigated. This is our second key policy message.

Finally, we also find that there is a trade-off in using a fixed budget to lower entry costs vs exit costs. Thus, our third policy message is that rupee-for-rupee entry subsidies raise value added less than exit subsidies, but the reverse is true for employment.

The broad mechanisms that we are proposing here are not new. It is well understood from the literature on sunk costs of entry (e.g. Hopenhayn, 1992; Hopenhayn and Rogerson, 1993; Roberts and Tybout, 1997; Das et al., 2007), that such costs discourage exit in response to bad shocks. Our main focus is to provide not just evidence consistent with such predictions (for example, we show that firms in high-performing states are more responsive to negative shocks than those in low-performing states) but also a quantitative evaluation of this critical mechanism in an important setting. Moreover, 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 a country's specific regulations or frictions (like labor regulations, bankruptcy regulations, government subsidies, and land market frictions), which can raise exit costs rather than on exit barriers as a whole.

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 (e.g. Besley and Burgess, 2004) and structural methods (e.g. Cooper and Willis, 2009).

In India, one of the main laws that regulates the firing of workers is the Industrial Disputes Act of 1947. Amongst other things, it puts additional restrictions on firing workers in firms with more than 100 workers. However, this law has been reformed differentially between states, leading to cross-state variation in labor adjustment frictions (Besley and Burgess, 2004). Thus, a large literature studies how firms located in states with lower frictions respond to shocks relative to those located in states with higher frictions (e.g. Adhvaryu et al., 2013; Chaurey, 2015; Aghion et al., 2008).

There are three main shortcomings to this approach. First, the (Besley and Burgess, 2004) index used to classify states as pro-worker or pro-business is imperfect and has been highly criticized (see Bhattacharjea, 2006). Second, the implementation of these laws is imperfect. Much is left to the discretion of the courts and authorities, making the outcomes uncertain.[8] The decisions of the lower courts are usually extreme and often overturned by the higher courts.[9] Thus, labor-reform indices based on the letter of the law and actual implementation of the law can potentially go in different directions. 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 focuses on the macro implications of labor regulations. Building on Cooper and Willis (2009), our approach is able to estimate labor adjustment costs in a broader way and quantify the macro implications of the same.

A related literature has documented the predominance of small firms in developing countries and their inability to grow large (e.g. Hsieh and Olken, 2014). The misallocation literature (e.g. Hsieh and Klenow, 2009, 2014) has argued that the frictions that keep firms small are the key to explaining the low productivity of firms in developing countries. Some papers have unpacked what these frictions are. Hasan and Jandoc (2010) highlights the role of labor regulations, but only for labor-intensive industries. More recently, Padmakumar (2022) has shown the role labor regulations played in keeping firms small by reducing transition probabilities sharply at the 100-worker cut-off. Akcigit et al. (2021) argues that part of the reason for the prevalence of small firms is 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. Martin et al. (2017) points to policy-induced promotion and protection of small-scale firms and Amirapu and Gechter (2020) to corruption as other potential factors.

Compared to this literature, we highlight the role that exit barriers play, in addition to factor adjustment costs, in hindering firm size, productivity, and causing misallocation. Note that while all the papers cited above study a specific friction, this paper studies exit barriers comprehensively– including labor and capital adjustment frictions and other barriers to exit. Consistent with our theory, Alfaro and Chari (2009) had found that the deregulation of entry barriers in India led to a

[8]Issues include whether the IDA covers only manufacturing, mines, and plantations as stated in the act, or not. Who is a regular worker protected by the laws versus a contract worker who is not covered by these laws?

[9]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.

thickening of the left tail of the firm size distribution but mattered little for firm growth.

There is much less work on the role of exit barriers other than the work on labor regulations. Exceptions include work on capital adjustment costs (e.g. Cooper and Haltiwanger, 2006), and bankruptcy costs in finance, as these costs act as exit barriers. Reducing 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 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 to discourage firm failure and therefore greatly affect the ability of economies to adjust (Bignon and Sgard, 2007). More recently, Li and Ponticelli (2022) shows that in China, the introduction of specialized bankruptcy courts led to the reallocation of labor out of zombie firms, firm entry, and growth in productivity.

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 put on hold during COVID. However, even the IBC has had limited success due to judicial bottlenecks and court congestion. 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), which focuses on frictions in the acquisition of land for manufacturing. Note that rather than constraining ourselves to a particular source of exit costs, we capture a plethora of measurable and unmeasurable 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. However, the analysis would be incomplete for developing countries and especially for India. First, in developing countries, there can be multiple factors that interact with each other and 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 prevent exit may be unmeasurable and thus ignored in existing analyses. Finally, the general equilibrium effects on entry and via the interaction of various policies regulating exit may be large. Our approach makes progress on all these fronts.

In sum, our contribution to the literature is as follows. First, we model exit barriers in a much more flexible and comprehensive manner than in the literature.[10] This is needed, as we show, to match features in the data. For example, capital is rarely adjusted downwards by an active firm or dormant firm in the Indian context. Second, we are the first to show that when reducing exit barriers, it may be vital to reduce them in the proper order – reducing exit costs like red tape before labor reforms – in order to limit adverse employment effects. Third, we find that in the

[10]Not only are there possibly asymmetric hiring and firing costs for labor (note firing costs create exit costs as firms need to shed workers to exit), these costs are there for capital adjustments as well. In addition, there is the possibility of a haircut or its opposite for capital at the time of exit. This reflects the possibility that selling capital while active may be more or less difficult than when exiting. Finally, there is a scrap value obtained when the firm exits. If this is negative, it means the firm is willing to pay this amount to leave. All of this allows for a wide array of frictions to contribute to exit barriers.

Indian context, spending a given budget to subsidize entry costs or to reduce exit costs by raising scrap value has tradeoffs in terms of value added and employment.

The paper proceeds as follows. In Section 2, we provide some details about the institutional context.[11] 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 their estimates. Section 7 presents our counterfactual exercises in partial equilibrium. Section 8 extends the model to general equilibrium by making the price index and expenditure endogenous, and shows how our counterfactuals are affected, while Section 9 concludes.

2 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 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 varies 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 central 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. Finally, India's regulatory framework is not the only obstacle to firm exit. Political interference, a clogged judicial system, strikes, lockouts, etc., can also prevent firm closures.

This section aims to highlight various factors, not all of which are observable, behind exit costs in India. Thus, it would be impossible to quantify, even roughly, the aggregate costs of barriers to firm exit using reduced-form techniques. In contrast, our approach identifies these costs through their impact on firm behavior, which is observed. We first illustrate the challenges faced by a firm wanting to exit first through a specific case study. Then, we highlight the complexities in the implementation of the two most important regulatory frameworks that might affect firm exit – i.e. labor and bankruptcy laws. In Appendix A, we present a detailed discussion of the history of these regulations.

[11] More information on this can be found in online Appendix A.

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

Nokia announced its plan to set up a plant in India in December 2004. At that point, it sold about a million phones a month in India, all imported from China. It aimed 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. In addition to a tax holiday, the location at the special economic zone in Sriperumbudur was only 33km away from the Chennai International Airport. Also, the ruling party in the state (AIADMK) 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 central and state political rulers. Production started in 2006.

Between 2006 and 2012, this factory became the poster child of capitalism. It 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.

The 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 factory's success attracted political attention as they saw the employees as a vote bank. A DMK-backed (the party in opposition to AIADMK) labor union gained ground around 2010.

There was tough competition in the international market as well. As the tax holiday ended, 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 was 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. Initially, Microsoft wanted to use the factory as a contract manufacturer for low-cost cell phones, but soon decided against it, and production came to a 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 it was required to pay the workers as long as the tax dispute continued. Some permanent workers took voluntary retirement and severance payments offered by the company. Nokia did this because it would need approvals from the government and an agreement with the labor unions in order to close the factory once the tax dispute got resolved. Lawyers say that "7 or 8 out of 10 such cases are rejected" as "welfare statutes look out for the interest of employees". They advised that getting these permissions is 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.[12] 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. It is worth noting that Nokia is far from the only multinational to find itself in such straits. GM and Ford also had a taste of trying to exit under Indian conditions.[13]

2.2 Labor Laws, Hiring, and Firing Labor

Labor regulation in India is governed by numerous laws, which vary significantly across states. For instance, Maharashtra has 48 labor laws, while West Bengal has 31. The Industrial Disputes Act (IDA) of 1947 is the most notable and frequently studied in Economics. See Besley and Burgess (2004) for more on this. Three points are worth noting:

1. Implementation vs. Legislation: The actual implementation of laws often diverges from their written form. A stringent IDA provision requires firms with over 100 workers to get government permission before dismissing employees. Obtaining this permission is complex and discretionary, leading to uncertain outcomes.

2. Judicial Backlog: Indian courts face severe backlogs, with over $100,000$ labor cases pending as of October 2020, 40% of which have been pending for over a year. Consequently, the efficiency of labor law enforcement varies across states and is influenced by both legal differences and court efficiency (Rao, 2019).

3. Uncertainty in Legal Decisions: Firms encounter significant uncertainty regarding potential legal disputes. The interpretation of labor laws has evolved over the past six decades, influenced by socio-political and economic changes. Sarkar (2019) documented that while specific statutes have remained relatively unchanged, judicial interpretations have shifted. Courts have sometimes issued contradictory rulings on similar cases within short time frames, oscillating in their rulings on which workers and industries (software engineers vs factory workers) should be covered by labor laws and when. Even the Supreme Court has overturned its own decisions numerous times. Details in Appendix A highlight this inconsistency further.

[12] For more institutional details, see Online Appendix A.

[13] See Reddif.com Business "GM, Ford switch off India ops but unable to exit", January 25, 2023.

2.3 Bankruptcy Laws

Enforcing creditor rights in India has historically faced significant judicial delays. This is partly due to complex and fragmented insolvency procedures under multiple laws, such as the Companies Act of 1956 and the Sick Industrial Companies (Special Provisions) Act of 1985. Since the early 1990s, various reforms have been attempted with limited success.

In 1993, Debt Recovery Tribunals (DRTs) were established to streamline the legal process. However, inadequate infrastructure and personnel soon led to these tribunals becoming clogged. In 2002, the Securitization and Reconstruction of Financial Assets and Enforcement of Security Interests Act (SARFAESI) allowed secured creditors to take possession of assets within 60 days of a loan default notice. Over time, court interpretations diluted the Act's effectiveness by, for example, granting borrowers the right to appeal, which hindered loan recovery. In 2016, the Insolvency and Bankruptcy Code (IBC) was introduced to further streamline the process by giving creditors control of assets upon initiating insolvency proceedings and imposing strict timelines for liquidation. However, the IBC has also seen limited success due to judicial bottlenecks and court congestion.[14] And as with labor laws, there has been a lack of clarity about bankruptcy laws and higher courts have frequently quashed orders of lower courts.[15]

3 Data

Our data comes from the Annual Survey of Industries (ASI), which provides plant-level data for registered manufacturing and repair units in all states of India except northeastern Arunachal Pradesh, Mizoram, Sikkim, and the island of Lakshadweep. ASI's sampling frame is based on the lists of registered factories maintained by each state.[16] The census sector, defined as those units employing 200 workers or more, is surveyed every year.[17] The sample sector, from which a representative sample is surveyed each year, contains the rest of the frame.[18]

We use the longitudinal version of the ASI, which is available from 1999 till 2018. Like many other establishment-level datasets, the ASI includes details of fixed assets, working capital and loans, employment, input items, products and by-products produced, other expenses, and receipts.

[14]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].

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

[16]The frame essentially has establishments with 10 workers or more and using power, or with 20 workers or more, without power. Therefore, the ASI does not capture the informal manufacturing sector.

[17]All units in the states of Manipur, Meghalaya, Nagaland, Tripura, and the Andaman and Nicobar Islands are also in the census sector. However, Indian firms may choose not to provide the data requested by the government. If so, they are placed on a list of non-compliers. This creates holes in the data over time, even for firms in the census sector.

[18]More details are available on the website of the Ministry of Statistics and Programme Implementation, Government of India.

Several features of this data make it uniquely useful for our purposes. First, the survey records its initial year of production. This feature allows us to accurately measure exit by tracking the mass of establishments of a certain vintage over time, as done in Hsieh and Klenow (2014). Second, the data records the status of responding establishments as either "active" or "dormant". "Dormancy" occurs when the firm exists with all its capital, but does not engage in production. This is an important feature because it is exactly what one would expect with high exit barriers: that is, the presence of establishments that want to exit but do not, and instead stay dormant, both with and without workers.[19] Third, the data records all details, such as factor payments, loans, and assets, even when an establishment is dormant, though the quality of the data for dormant firms tends to be worse. We exploit these features of the data in our analysis to estimate exit costs.

4 Facts

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

Fact 1: Entry and exit shares are highly correlated, vary across states, are persistent over time, and correlate positively with measures of performance.

There is significant variation in formal manufacturing activity across Indian states. To illustrate this, we compute plant entry shares in major states of India.[20] We define the 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, relative to the state's population share.[21] Thus, if a state's entry share is greater (lower) than 1, then it attracts more (fewer) entrants relative to its size. Figure 2a shows the map of India and colors the states by their entry shares, with darker states having higher entry shares. Figure 2b shows that entry shares by state are not only different, but are strongly positively correlated with their exit shares.[22] States with higher exit shares, represented in red, have higher entry shares, and vice-versa. This makes sense: potential entrants will not want to enter states with restrictive exit conditions, and in steady state, entry and exit rates should be the same. It is immediately apparent that some states are disproportionately more attractive

[19] Dormant firms without workers are dropped from the sampling frame after three years.

[20] As the ASI records plants' initial year of production, this is straightforward to do.

[21] For our analyses, we group Andhra Pradesh and Telangana, Punjab and Chandigarh, Haryana and Delhi, Karnataka and Goa. We exclude North-Eastern states and Jammu and Kashmir from our analyses because the sample data is very sparse.

[22] 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. The 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 normalize the 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. For more details on the calculation, please see section B.1 in the Appendix.

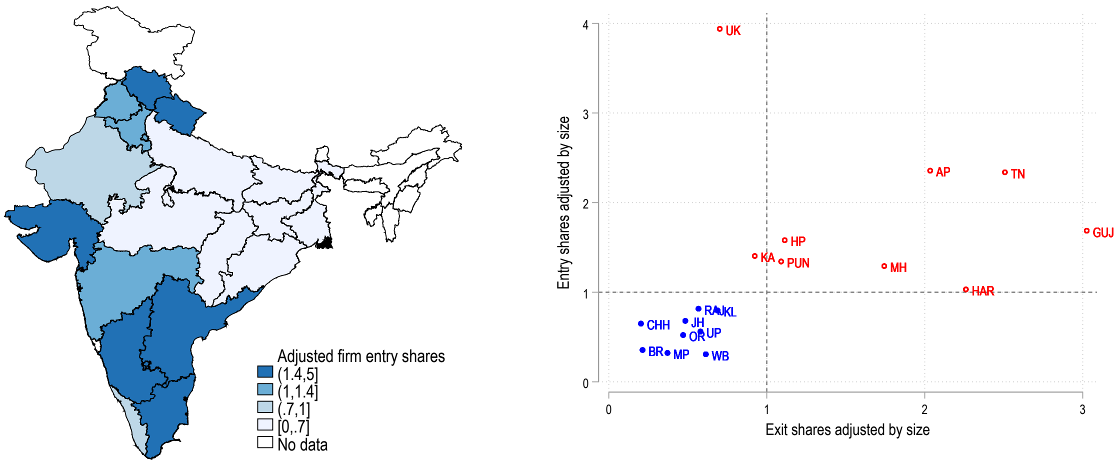
to industries relative to their size. In particular, entry into the states of Gujarat, Maharashtra, Andhra Pradesh, Karnataka, and Tamil Nadu is higher than that into the BIMARU (meaning sick in Hindi) states of **Bi**har, **Ma**dhya Pradesh, **R**ajasthan, **U**ttar Pradesh. West Bengal and Kerala also have low entry shares, not surprising given their tendency to have communist governments. Moreover, as shown in Figure B.1, 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.

We will not be able to conduct our analysis (both structural and reduced-form) below at the state level, as not all states have enough plants for us to do so. For this reason, we will classify them into two groups. In particular, we classify states as *high-performance* or HP for short (those with size-adjusted entry share at least 1) and *low-performance* or LP for short (those with size-adjusted entry share below 1.) Below, we also look at a number of other patterns that are in line with our above classification. While we acknowledge that our classification is based on endogenous variables, our goal is simply to illustrate heterogeneity. In our structural model, we use other well-identified moments to identify exit costs and economic fundamentals.

Do entry shares also correlate positively with the extent of resource misallocation in states? The extent of misallocation can be thought of as capturing state-specific institutional frictions without being specific about the exact sources of distortions. Following the literature (Lucas, 1978; Bento and Restuccia, 2021), we use the elasticity of plant size – defined as the number of non-managerial workers – with respect to plant revenue residuals as a measure of misallocation for each state[23]. Intuitively, more resources will be allocated to plants with higher productivity or demand shocks, so one would expect a higher elasticity of plant size with respect to plant revenue residuals in states where resources can adjust freely. Figure B.2 shows that entry shares and the extent of misallocation are indeed related – states with an entry share above 1 have lower misallocation and vice versa. Furthermore, entry shares are negatively correlated with some specific institutional barriers to exit. For instance, Figure B.3 shows that states with higher entry shares have fewer pending civil cases per judge in their high courts on average and vice versa. Figure B.4 shows that states with higher entry shares have fewer workers involved in strikes on average, and vice versa.

One would expect HP and LP states to differ in other dimensions as well - the profitability and age distributions of plants should also differ, as might their response to shocks like a more streamlined insolvency procedure for financially distressed plants. We look for such evidence below.

[23]It must be noted that revenue residuals are different from total factor revenue productivity (TFPR). Following Foster et al. (2016), revenue residuals reflect total factor physical productivity (TFPQ) and plant-level demand shocks, and do not include plant-level prices (see section B.3 in the appendix). Hence, they vary across plants within an industry due to differences in TFPQ and demand shocks, not plant-level prices or mark-ups. We prefer revenue residuals over TFPR, since TFPR can be uncorrelated with TFPQ: in settings like Melitz (2003), high-TFPQ plants charge lower prices, leaving TFPR relatively unchanged compared to low-TFPQ plants that charge higher prices. This concern does not apply to revenue residuals as they do not contain plant-level prices and are therefore positively correlated with TFPQ. Our measure of revenue residuals also aligns with the productivity proxy in our structural model.

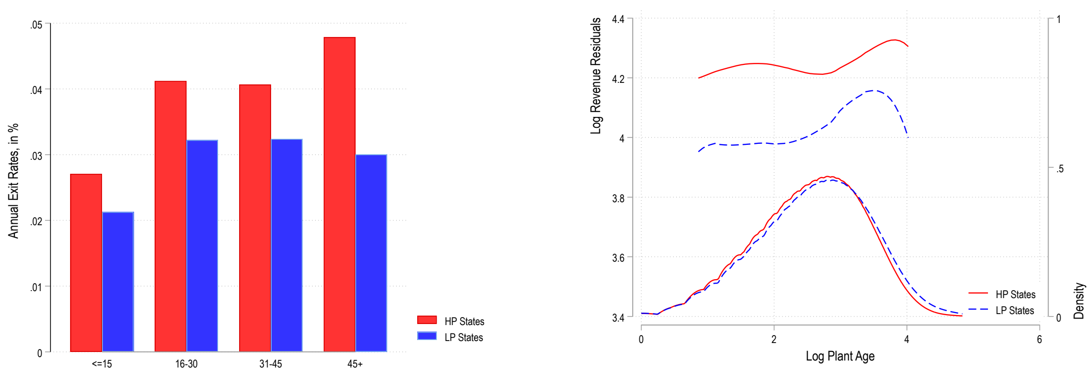


(a) Size-adjusted entry shares (b) Size-adjusted entry and exit shares

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. The size-adjusted exit share of state *s* is analogously defined. Panel (a) shows size-adjusted plant entry shares in Indian states averaged from 1999 to 2018. High-performance states are those with size-adjusted entry share greater than or equal to 1 (the two darker shades of blue). Low-performance states are those with size-adjusted entry shares less than 1 (lighter shades of blue). Panel (b) shows the relationship between size-adjusted entry and exit shares for states.

Fact 2: Exit rates are lower in LP states. There are more old low-productivity firms in LP states than in HP states, and age and productivity are non-monotonic in LP states but not in HP ones.



(a) Exit Rates in LP vs HP States (b) Profitability versus Age

Figure 3: Annual Plant Exit Rates and Revenue Residuals in High and Low-Performance States

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 low-performance states across cohorts of plants of different ages, especially for old plants.[24]

[24]For more details on the calculation, please see section B.1 in the Appendix. Figure B.5 provides a comparison of annual exit rates in the formal and informal manufacturing sectors for high- and low-performance states.

The consequences of exit costs are seen in the distribution of revenue residuals of plants, a proxy for TFPQ. The right panel of Figure 3 examines the cross-sectional relationship between plant revenue residuals and plant age (left axis), as well as the age distribution of plants (right axis). There are more older plants in LP states. In 1999, the 99th percentile of the plant age distribution was 95 in LP states compared to 68 in HP states, and this difference between the two state groups persisted over time. In addition, productivity increases with age in HP states, but not in LP states. Consistent with higher exit costs in LP states, there exist some really old plants with low productivity in LP states, but not in HP states.

Fact 3: Bankruptcy reforms raised exit among highly leveraged and concurrently distressed firms, and had a greater impact in LP states.

In 2002, the Government of India introduced a new law called the Securitisation and Reconstruction of Financial Assets and Enforcement of Security Interest (SARFAESI) Act that allowed secured creditors to take possession of assets within 60 days of a loan default notice. Such a reform should ease the exit of financially distressed and highly leveraged plants by making it more straightforward for the creditors to take over and liquidate the assets. This should be more so where exit was harder to begin with. In this section, we empirically test this hypothesis and further show that the responses to this bankruptcy reform were larger in low-performing states where the institutional mechanisms to exit are expected to have been worse. Thus, we would expect more exit when exit is made easier, and more so in LP states.

The dependent variable is an indicator of whether the plant has exited. In particular, if T is the last year in which plant i shows up in the panel and t_0 is the initial year of production, then $1\{Exit_{ijst}\} = 1$ for $t > T$ and 0 for $t_0 \leq t \leq T$. We define two indicator variables, $\mathbb{1}\{HighLeverage_i\}$ and $\mathbb{1}\{Distressed_i\}$, to capture whether a plant was highly leveraged or economically distressed in the pre-SARFAESI period (1998-99 to 2001-02). Following Vig (2013) and Alok et al. (2022), we compute the leverage ratio of a plant in any year as the ratio of its liabilities to assets. A plant is characterized as highly leveraged ($\mathbb{1}\{HighLeverage_i\} = 1$) if its average leverage ratio in the pre-SARFAESI period is greater than the national median during the same years. Similarly, a plant is characterized as being financially distressed ($\mathbb{1}\{Distressed_i\} = 1$) if its profits in the pre-SARFAESI period are in the bottom decile of the national distribution. Finally, $1\{Post_t\} = 1$ for years starting from 2002-03, i.e., post the bankruptcy reforms.

All regressions reported in Table 1 include plant, industry×year, and state×year fixed effects. Bankruptcy reform would directly affect leveraged plants. Column (1) shows that after the implementation of SARFAESI, highly leveraged plants indeed had 0.8 percentage points (pp) higher exit rates compared to the baseline exit rate of 6.6%. Column 2 shows that this effect is coming from firms that are both highly leveraged and distressed, while columns 3 and 4 show it is coming from LP, not HP, states. Columns 5-7 repeat models 2-4 but also include a high-leverage × year fixed-effect to account for differential trends among highly leveraged plants and show that our results are robust.

Table 1: Effect of SARFAESI on Exit Rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				$\mathbb{1}\{Exit_{ijst}\}$			
$\mathbb{1}\{Post_t\} \times \mathbb{1}\{HighLeverage_i\}$	0.008*	0.001	0.002	-0.000			
	(0.003)	(0.004)	(0.005)	(0.006)			
$\mathbb{1}\{Post_t\} \times \mathbb{1}\{Distressed_i\}$		0.013	0.021	-0.004	0.013	0.021	-0.004
		(0.010)	(0.013)	(0.017)	(0.010)	(0.013)	(0.017)
$\mathbb{1}\{Post_t\} \times \mathbb{1}\{HighLeverage_i\} \times \mathbb{1}\{Distressed_i\}$		0.045***	0.028	0.078***	0.045***	0.028	0.079***
		(0.014)	(0.017)	(0.022)	(0.014)	(0.017)	(0.023)
Avg. $\mathbb{1}\{Exit_{ijst}\}$ 1998-99 to 2001-02	6.6%	5.7%	5.9%	5.3%	5.7%	5.9%	5.3%
N	306448	267941	173639	94301	267941	173639	94301
No of Plants	34276	29961	19412	10549	29961	19412	10549
Plant, Industry×Year, & State×Year FE	✓	✓	✓	✓	✓	✓	✓
High-leverage×Year FE					✓	✓	✓
Sample	All states	All states	HP states	LP states	All states	HP states	LP states

Notes: Each observation is an establishment or a plant i in industry j, state s, year t. All models are estimated between the years 1998-99 and 2006-07. $\mathbb{1}\{Exit_{ijst}\}$ is an indicator that equals 1 for all years after the last year when establishment i shows up in the panel. $\mathbb{1}\{Post_t\}$ is an indicator that equals 1 for years after 2002-03. $\mathbb{1}\{HighLeverage_i\}$ is an indicator that equals 1 if the average liabilities to assets ratio of establishment i during 1998-99 and 2001-02 is greater than the median of the national distribution. $\mathbb{1}\{Distressed_i\}$ is an indicator that equals 1 if the average profits of establishment i between 1998-99 and 2001-02 are in the bottom decile of the distribution. Robust standard errors clustered at the plant level are reported in parentheses.

Fact 4: Adjustment of regular workers in response to shocks is lower in LP states.

In this section, we examine whether labor adjustment is harder in low-performance states than in high-performance states by comparing how plants in different states adjust labor in response to similar shocks to plant performance. This is what we would expect if firing costs are higher in LP states. We follow Guiso et al. (2005) to isolate unanticipated changes in gross value added (GVA) that cannot be explained by plant-specific characteristics and aggregate fluctuations. In particular, we regress the inverse sine transformation of GVA[25] 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.

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

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.

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

The outcomes of interest here are logarithms of regular employment, contract employment, and managerial employment at the plant level. $\mathbb{1}\{LP_s\}$ is a dummy variable that takes a value equal to 1 if the plant is located in an LP state. In order to minimize omitted variable bias, we incorporate

[25]We take the IHS (Inverse Hyperbolic Sine) defined as $ln(x + (x^2 + 1)^{.5})$ instead of $log(x)$ because in the data GVA is sometimes negative so that $log(x)$ may not be defined. Results are similar if we rescaled GVA to be positive.

a rich set of covariates that are both time-invariant and time-varying in the regression specification. 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 firm age.

With these controls, β_1 measures the average impact of negative shocks on employment in the subsequent year by plants in high-performance states. β_2 captures the differential response to negative shocks in low-performance 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 2: Impact of negative shocks on employment in high and low-performance states

Dependent variable:	log Employment					
	(1) Regular Workers	(2) Regular Workers	(3) Contract Workers	(4) Contract Workers	(5) Managers	(6) Managers
$\mathbb{1}\{Neg\_shock_{it-1}\}$	-0.086***	-0.091***	-0.122***	-0.122***	-0.081***	-0.083***
	(0.003)	(0.004)	(0.009)	(0.011)	(0.003)	(0.004)
$\mathbb{1}\{Neg\_shock_{it-1}\} \times \mathbb{1}\{LP_s\}$		0.015*		-0.002		0.007
		(0.007)		(0.019)		(0.007)
N	223169	223169	106809	106809	202645	202645

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 reports estimates of β_1 and β_2 from specification (1). Column 1 of Table 2 indicates that plants reduce their regular employment by 8.6% on average when faced with a negative shock in the previous year. However, plants in low-performance states are less sensitive to these shocks, as shown in column 2. In particular, a negative shock reduces average regular employment in the subsequent year by only 7.6% in low-performance states, compared to 9.1% in high-performance states. Columns 3 and 5 show that a negative shock reduces average contract and managerial employment in the subsequent year by 12.2% and 8.1%, respectively. There is no statistically significant difference between how high and low-performance states adjust their contract and managerial employment in response to negative shocks[26]. This makes sense as regular workers are protected by the IDA, not contract workers or managers.

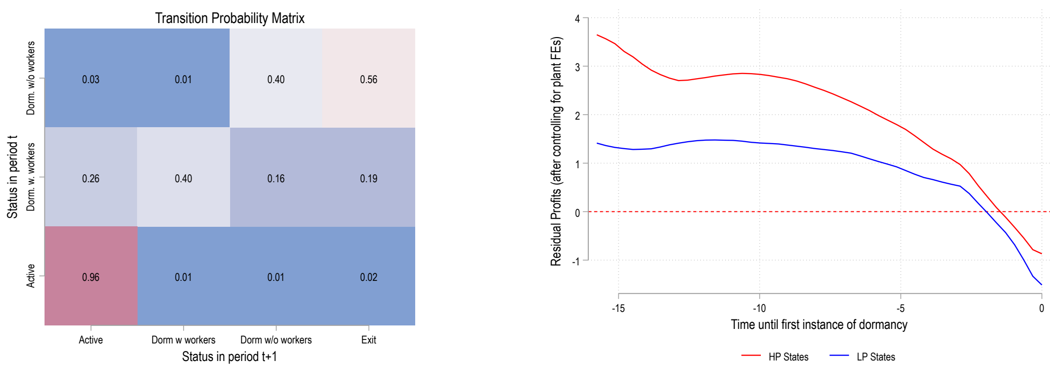
Labor laws make firing particularly hard for plants employing more than a hundred workers. Therefore, next, we show that the labor adjustment frictions in low-performance states are coming from larger plants. To do so, we define a dummy variable $\mathbb{1}\{Above100_{it-1}\}$ that equals 1 for plants employing more than 100 regular workers in year $t-1$ and is 0 otherwise. Then, we estimate a triple differences (saturated) version of the model in (1). Columns 1 and 2 of Table B.2 in the Appendix show that it is the large plants – those with more than 100 regular workers – that drive

[26]These patterns are robust even if we make the bins of GVA shocks finer. See Table B.3 in the Appendix for details.

the sluggish response of regular employment to negative shocks in low-performance states. Columns 3 and 4 of Table B.2 indicate no statistically significant difference in how large and small plants adjust their contract and managerial employment following negative shocks to value-added.

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)[27], and dormant without workers (those existing with fixed assets but not maintaining staff and not producing)[28]. 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 the plant fixed effects. Second, we rescale 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 the transition probabilities of plants between the different states. Of the plants that are active in any period, the probability that they continue to remain active is very high (=96%), 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

[27]The ASI survey manual says "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."

[28]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."

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[29]. Based on these transition probabilities, we postulate that dormancy is a path to exit for plants.

Plants would be expected to enter dormancy as a result of losses. The right panel of Figure 4 plots the profits of active plants as they approach dormancy. Two aspects are worth noting. First, on average, plants in low-performance states make lower variable profits than plants in high-performance states en route to dormancy. Second, plant profits fall as they approach dormancy, and variable profits turn negative before they become dormant, slightly earlier in low-performance states. Note that fixed costs are not included in variable costs, so firms would be making lower total profits than indicated by their variable profits alone.[30]

5 Model

In this section, we develop and quantify a theoretical model to estimate exit frictions and quantify their implications for aggregate productivity. We build on the models of firm dynamics (e.g. Roberts and Tybout, 1997; Melitz, 2003; Das et al., 2007; Aw et al., 2008), models of labor market frictions (e.g. Hopenhayn and Rogerson, 1993; Poschke, 2009; Cooper and Willis, 2009; Cooper and Haltiwanger, 2006), and models of firm exit (e.g. Ryan, 2012; Golombek and Raknerud, 2018).

The basic structure of our model is as follows. At the beginning of each period, new firms pay a fixed cost to enter. Both new entrants and incumbents then realize their productivity levels and scrap values. In our model, firms are heterogeneous in their productivity, which evolves according to an AR(1) process. Knowing their realizations of scrap value and productivity, firms can compare their expected payoff from staying versus exiting and choose the better option. If they choose to stay, they choose their target input levels, knowing there are convex adjustment costs. These targeted levels need not be attained due to uncertainty. Following this, firms realize their actual input levels and the fixed cost of production. Based on these, they choose either to pay this fixed cost and produce output or not pay and remain dormant. Then, we move to the beginning of the next period. Figure 5 shows the timing of events in each period.

Thus, we divide firms' decision making into a static component, where firms maximize their short-run profits by sourcing intermediate inputs, and a dynamic component, where they choose to

[29]Since we have data until 2018, we check if they show up again in the data in the next 11 years. A plant could not show up 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.

[30]As shown in Section B.9 in the appendix, we also show that on the path to dormancy, firms find it easier to reduce regular workers (but not managers or contract workers) in high inflation times, and this is more so for LP states. This makes sense as a firm can't cut wages of regular workers, and it is hard to fire them, but can fail to raise wages with inflation, thereby encouraging regular workers to leave.

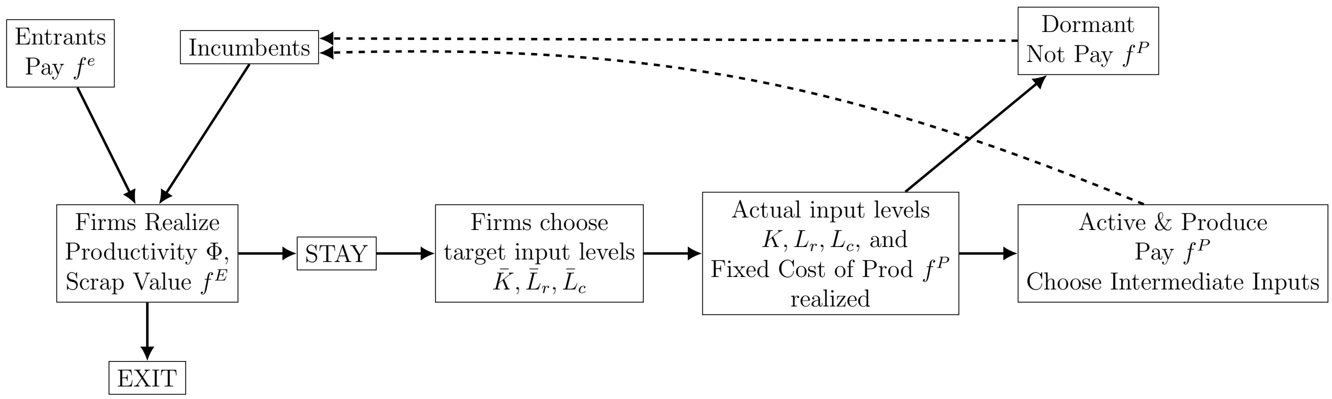


Figure 5: Timing of Events

be dormant or exit in the presence of exit costs, make production decisions in the presence of fixed costs, and adjust inputs, knowing that input adjustment costs are convex.

Two frictions distort resource allocation. First, low-productivity firms shed factors gradually due to convex input adjustment costs, which moves the allocation of factors away from efficient firms. Second, convex adjustment costs and additional exit costs make firms stay in the market longer, albeit dormant, as they search for a path to exit. These dormant firms, sometimes called Zombie firms, prevent scarce resources, such as capital and land, from reallocating to more productive firms. We provide formal details of the model next.

5.1 Production

Firms use labor, capital, and intermediate inputs to produce output. Motivated by the institutional context and the reduced-form evidence that regular workers are harder to fire than contract workers and managers, we differentiate between regular labor (i.e. regular, non-managerial workers, denoted by L_{rt}) and non-regular labor (contract workers and managers, denoted by L_{ct}).[31] The two types of labor are imperfect substitutes, subject to hiring and firing costs.

In addition, firms can adjust their capital, K_t, subject to convex adjustment costs, but intermediate inputs, I_t, are freely chosen in every period. Wages of both types of labor (w_r, w_c) and the price of intermediate inputs, r_I, are exogenously determined.

The production function is Cobb-Douglas in the three inputs, and firms are heterogeneous in their productivity, ϕ_{it}. A firm's output is given by

$$Y_{it} = \phi_{it} L_{it}^{\alpha_L} I_{it}^{\alpha_I} K_{it}^{\alpha_K}, \qquad \alpha_L + \alpha_I + \alpha_K = 1, \tag{2}$$

where $L_{it} = L_{cit}^{\alpha_{Lc}} L_{rit}^{\alpha_{Lr}}$, is an index of the two types of labor. Further, we assume that a firm's

[31]This classification also makes it easier to deal with the fact that many firms have no contract workers which would otherwise create problems given the Cobb Douglas form of the production function used.

productivity evolves over time according to an AR(1) process:

$$\ln \phi_{it} = \gamma_0 + \gamma_1 \ln \phi_{it-1} + \epsilon_{it}. \tag{3}$$

5.2 Static Decisions

The market structure is monopolistic competition, and firms face a demand function with a constant elasticity σ,

$$D(p) = p^{-\sigma} E. \tag{4}$$

Here, E is the aggregate demand[32], and p is the price charged by the firm.

In each period, given labor, L_{ct}, L_{rt}, and capital, K_t, firms make a static decision to maximize profits by choosing intermediate inputs and price.

$$\max_{I_{it},p} \quad p^{1-\sigma} E - r_I I_{it} \qquad \text{s.t.} \quad p^{-\sigma} E = \phi_{it} L_{it}^{\alpha_L} I_{it}^{\alpha_I} K_{it}^{\alpha_K}.$$

After solving for the optimal choice of I_{it}, we substitute it back and get the per-period value-added as a function of L_{ct}, L_{rt}, and K_t. Per-period value-added takes the form in Equation (5):

$$VA(\phi_{it}, L_{c,it}, L_{r,it}, K_{it}) = \Gamma \left(E^{\frac{1}{\sigma-1}} \phi_{it} L_{it}^{\alpha_L} K_{it}^{\alpha_K} \right)^{\frac{\frac{\sigma-1}{\sigma}}{1-\alpha_I \frac{\sigma-1}{\sigma}}}. \tag{5}$$

Here, Γ is a constant.[33] The per-period value-added of firm i is increasing in its productivity ϕ_{it}, labor employment L_{it}, and capital K_{it}. Define, $\tilde{\phi}_{it}$, be the profitability of firm i at t, $\tilde{\phi}_{it} = \Gamma \left(E^{\frac{1}{\sigma-1}} \phi_{it} \right)^{\frac{\frac{\sigma-1}{\sigma}}{1-\alpha_I \frac{\sigma-1}{\sigma}}}$. The evolution of profitability is estimated as follows.

$$\ln \tilde{\phi}_{it} = \tilde{\gamma}_0 + \tilde{\gamma}_1 \ln \tilde{\phi}_{it-1} + \tilde{\varepsilon}_{it} \tag{6}$$

5.3 Dynamic Decisions

5.3.1 Labor Adjustment and its Costs

The data suggest that labor adjustment costs are convex. Recall that in Section 4, we showed that labor adjusts gradually in response to shocks. Hence, we assume a quadratic functional form for labor adjustment costs. If the targeted employment level of the firm is $(\bar{L})$ and employment in the

[32] E can be normalized to 1 for now as we start with partial equilibrium where income and the price index are given.

[33] $\Gamma = \left(1 - \alpha_I \frac{\sigma-1}{\sigma}\right) \left(\frac{1}{r_I} \alpha_I \frac{\sigma-1}{\sigma} \right)^{\frac{\alpha_I \frac{\sigma-1}{\sigma}}{1-\alpha_I \frac{\sigma-1}{\sigma}}}$.

last period is (L_{t-1}), then adjustment costs take the following functional form:

$$A \times \left(\frac{\bar{L}_t}{L_{t-1}} - 1 \right)^2 \tag{7}$$

The quadratic term captures the idea that hiring or firing a large proportion of the workforce at one time is harder. As specified below, A will be allowed to differ across firms above the IDA threshold and below it, across regular and contract workers, and depending on whether workers are being hired or fired. This will permit adjustment costs to differ by worker type (regular or contract), firm size (large and small), and the kind of adjustment, up or down.

Hiring Costs: Hiring costs reflect the cost for firms to post vacancies and find and hire the best-qualified workers. For existing firms, hiring costs of regular ($j = r$) and non-regular ($j = c$) workers take the following form[34]:

$$\underbrace{[c_{Hj} \log(1 + L_{jt-1})]}_{H_j} \left(\frac{\bar{L}_{jt}}{L_{jt-1}} - 1 \right)^2, \qquad j = r, c, \tag{8}$$

where, c_{Hr} and c_{Hc} are parameters. As regular and non-regular workers are employed through different channels, their hiring costs are potentially different. The term in square brackets, H_j, allows the hiring cost to both depend on firm size and differ for regular and non-regular workers.

Firing costs: Firing costs are meant to reflect the frictions arising from various factors like, but not limited to, size-based labor laws, the presence of labor unions, local politics, and so on. Though contract labor and managers (non-regular workers) are not protected by labor laws, firing them successfully can take time as workers adapt many strategies[35] to retain their jobs. The firing cost of non-regular workers takes the same form as hiring costs:

$$\underbrace{[c_{Fc} \log(1 + L_{ct-1})]}_{F_c} \left(\frac{\bar{L}_{ct}}{L_{ct-1}} - 1 \right)^2 \tag{9}$$

The above functional form ensures that for a given proportional change in workers, larger firms have higher firing costs. Since regular workers in firms with more than 100 regular workers are additionally protected by labor laws, we allow firing costs for regular workers to be discretely different at that threshold. In particular, the term multiplying the quadratic term is defined as:

$$F_r = \begin{cases} c_{Fr}^L \log(1 + L_{rt-1}) & \text{if } L_{rt-1} \geq 100 \\ c_{Fr}^S \log(1 + L_{rt-1}) & \text{if } L_{rt-1} < 100 \end{cases} \tag{10}$$

[34]For entrants, we assume that the hiring cost is zero, that is, $H_j = 0$.

[35]As discussed before, fired workers usually approach the court, which takes time to adjudicate matters, and many times, courts reclassify contract workers as regular workers and reinstate them.

In equations (8), (9), and (10), the little c's are parameters that we will estimate.

Realized Employment: The realized employment is subject to an employment shock that captures uncertainties in factor adjustment beyond the firm's control: workers leaving for personal reasons or not all job offers being accepted. We assume that the log actual employment of regular and non-regular workers is distributed log-normally with means $log(\bar{L}_{ct})$ and $log(\bar{L}_{rt})$, and standard deviations $\sigma^{\varepsilon}_{Lc}$ and $\sigma^{\varepsilon}_{Lr}$ respectively. Thus, implicitly, the targeted employment level of firms is the median realized employment.

$$\log L_{jt} \sim \mathcal{N}(\log(\bar{L}_{jt}), \sigma^{\varepsilon}_{Lj}) \qquad j = r, c. \tag{11}$$

5.3.2 Capital Adjustment and its Costs

Capital adjustment costs take the same functional form as labor adjustment costs. They are:

$$\begin{cases} c_{HK} \log\left(1 + K_{t-1}\right)\left(\frac{\bar{K}_t}{K_{t-1}} - 1\right)^2 & \text{if } \bar{K}_t \geq K_{t-1}, \\ c_{FK} \log\left(1 + K_{t-1}\right)\left(\frac{\bar{K}_t}{K_{t-1}} - 1\right)^2 & \text{if } \bar{K}_t < K_{t-1}. \end{cases} \tag{12}$$

Here, $\bar{K}_t$ denotes the target level of capital stock. Further, as before, we will estimate separate parameters c_{HK}, and c_{FK} for hiring and firing capital, respectively. Finally, as with labor, we assume that log of realized capital is distributed log-normally with mean $log(\bar{K}_t)$ and standard deviation σ^{ε}_{K}.

5.3.3 Dormancy vs Production, and their Costs

After firms realize their levels of capital and labor, they must decide whether to produce or be dormant. This depends on a stochastic draw of the fixed cost of production, in addition to realized input and productivity levels. The fixed production cost depends on the firm's state in the previous period. Denote these fixed costs as f^{DP} and f^{PP} depending on whether the firms were dormant or active in the last period. We assume that f^{DP} and f^{PP} are independent and log-normally distributed with means μ_f^{PP} and μ_f^{DP}, and variance σ_P^2.

Depending on input levels and the fixed cost shock, the firm will choose to pay the fixed cost and produce, or be dormant and not pay this cost. Dormant firms must still pay their factors of production. Dormancy has two roles. First, firms can adjust their labor employment gradually during dormancy, thereby avoiding the large firing cost of laying off all their workers. Second, staying in dormancy gives firms who have received a large negative shock but who have hopes that this is temporary the option of becoming active when times improve.

5.3.4 Entry and Exit

At the beginning of 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 behaves as an incumbent. They realize their productivity level, ϕ, and their scrap value f^E. If firms exit, they get their scrap value net of adjustment costs. Hence, a low f^E reduces the likelihood of exit. Firms exit when they realize a high enough scrap value draw, f^E, net of adjustment costs relative to expected future profits. When firms exit, they lay off workers and sell their capital subject to the same adjustment cost specified in Section 5.3, but with a potentially different parameter value for the capital divestiture cost c^E_{FK}. Hence, upon exiting, firms get their realized scrap value, plus the value of the sale of depreciated capital, net of adjustment costs incurred, denoted by $\tilde{f}^E$. Hence:

$$\tilde{f}^E = f^E + p_K \delta^K K_{t-1} - c^E_{FK} \log(1 + K_{t-1}) - c_{Fc} \log(1 + L_{ct-1}) - c_{Fr} \log(1 + L_{rt-1}) \tag{13}$$

Allowing exiting firms to have different exit costs helps accommodate the possibility of distress sales, etc. We assume that the scrap value draw, f^E, follows a logistic distribution with mean μ^E_f and scale parameter σ_E. These shocks help us better match reality in which similar firms may make different exit choices for reasons outside our model. For example, a distressed firm might suddenly get lucky because of a sudden offer for its brand or an unexpected court judgment, thereby reducing its exit costs.

If firms choose to stay, they choose their target labor and capital levels, taking into account the relevant adjustment costs. After subsequent realizations of actual input levels and fixed production costs, firms choose to produce or be dormant and, in both cases, start the next period as incumbents. Firms enter till the expected profits from doing so are zero. We assume that the capital stock in the economy is fixed at $\bar{K}$.[36] Thus, the mass of entrants M^e and price of capital 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 therefore pinned down by a zero ex-ante profits condition. In our counterfactuals below, we explore how sensitive our counterfactuals will be to raising the capital supply elasticity upwards from zero.

5.4 Value Functions

Given the structure of the model, we can now describe the value functions of firms and their policy functions. Let s_t be the state of the firm: $s_t = (\tilde{\phi}_t, L_{ct-1}, L_{rt-1}, K_{t-1}, S_{t-1})$. Here, S_t is the status of the firm in period t, which can be either active and producing (P) or dormant (D).

We begin by describing the value function for any period $t \geq 1$ and then derive the value function at period $t = 0$ by backwards induction.

[36]Note that this assumption does not affect our estimates. We allow for an increasing supply of capital in our simulations later on.

For period $t \geq 1$

For any period $t \geq 1$, the value function of a firm, denoted by V, is the maximum of what it obtains if the firm stays or exits. If a firm exits, it obtains its realized scrap value plus the value of its capital net of adjustment costs ($\tilde{f}^E$). Let the firm's value from staying be $V^S(s_t)$. Then,

$$V(s_t) = \mathbb{E}_{\{f^E\}}\left\{\max_{d=E,S}\{\tilde{f}^E, V^S(s_t)\}\right\} \tag{14}$$

and,

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

The firm chooses its target levels of inputs denoted by $\bar{L}_{rt}, \bar{L}_{ct}, \bar{K}_t$. We integrate over the randomness in the realization of input levels. Once the actual levels are realized, it chooses whether to produce or be dormant. $R(\cdot)$ is the value-added net of fixed production cost. S_{t-1} indicates the status in the previous period, either production $S_{t-1} = P$ or dormancy $S_{t-1} = D$.[37]

$$R(\tilde{\phi}_t, L_{ct}, L_{rt}, K_t, S_t, S_{t-1}) = \mathbb{1}\{S_t = P\}\{VA(\tilde{\phi}_t, L_{ct}, L_{rt}, K_t)\} - \mathbb{1}\{S_{t-1} = P\}f^{PP} - \mathbb{1}\{S_{t-1} = D\}f^{DP}$$

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 an initial log-normal distribution with a mean $\frac{\tilde{\gamma}_0}{1-\tilde{\gamma}_1}$ and a variance $\frac{(\sigma^{\varepsilon}_{\gamma})^2}{1-\tilde{\gamma}_1^2}$. In period 0, the value function of a firm is V_0, where:

$$V_0(\tilde{\phi}_0) = \max_{d=E,S}\Big\{0, \max_{L_r,L_c,K}\{VA(\tilde{\phi}_0, L_c, L_r, K) + \delta^V \mathbb{E}_{\tilde{\phi}_1|\tilde{\phi}_0} V(s_1)\}\Big\}$$

Firms choose to stay in the market ($d = S$) when the value of doing so is greater than zero, otherwise, firms exit the market immediately. Firms enter till there are zero ex-ante profits because of free entry. Therefore, the expected payoff of entry equals the entry cost.

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

[37] The value-added is defined in Equation (5).

6 Estimating the Model

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), input shares in production (α_L, α_I, α_K, α_{Lc} and α_{Lr}), labor and capital adjustment cost parameters (c_{Hc}, c_{Fc}, c_{Hr}, c^L_{Fr}, c^S_{Fr}, c_{HK}, and c_{FK}), parameters of the distributions of shocks to labor and capital (σ^ε_K, σ^ε_{Lr}, σ^ε_{Lc}), the mean and variance of the fixed cost of production draws (μ^{PP}_f, μ^{DP}_f, σ^2_P), the mean and variance of the scrap value distribution (μ^E_f, σ^2_E), the firing cost of capital when the firm exits c^E_{FK}, and the productivity evolution parameters ($\tilde{\gamma}_0$, $\tilde{\gamma}_1$, $\tilde{\sigma}^\varepsilon_\gamma$).

Of these, we calibrate δ^V, δ^K, the input shares α's, factor prices w_c and w_r, and the demand elasticity σ. The remaining 19 parameters, i.e.,

$$\theta = \{\tilde{\gamma}_0, \tilde{\gamma}_1, \tilde{\sigma}^\varepsilon_\gamma, c_{Hc}, c_{Fc}, c_{Hr}, c^L_{Fr}, c^S_{Fr}, c_{HK}, c_{FK}, \sigma^\varepsilon_{Lc}, \sigma^\varepsilon_{Lr}, \sigma^\varepsilon_K, \mu^{PP}_f, \mu^{DP}_f, \sigma_P, c^E_{FK}, \mu^E_f, \sigma_E\}$$

are estimated using the dynamic model.

We want to capture key differences in institutions and economic conditions between the high-performance and low-performance states.[38] Hence, we allow some key parameters to be different between these regions. These are the wages of workers (as wages are higher in high-performance states), the intercept of the profitability process (as productivity could evolve differently in well run and poorly run states), firing costs of regular and non-regular workers (as there may be differences in implementing the law across these groups of states), and the mean of the scrap value draws (as their economic climate may differ). We are guided by the data and the empirical patterns reported in Section 4 in making these choices while trying to minimize the number of parameters in the model.

For estimation, we set up the data as follows. We only use data from 1999 to 2008. This is because we want to avoid any shocks that might contaminate the model due to the global financial crisis. Since we need historical information on productivity, which can only be inferred from active firms, we include firms in our data only when they start producing. We also drop the firms that appear in the data only once, as our estimation procedure relies on having at least two years of data on a firm. To deal with macro shocks such as inflation and differences across industries, we homogenize the data by removing industry-year fixed effects from log value added.

6.1 Estimation Procedure

Since models of firm dynamics cannot usually be solved in closed form and therefore cannot be directly estimated, indirect inference procedures are typically used (e.g. Cooper and Haltiwanger, 2006). This involves specifying an auxiliary model that mimics the structural model. Next, data is simulated from the structural model using an initial guess ($\hat{\theta}_0$) of the structural parameters (θ). Then, the estimation objective is to search for values of structural parameters such that the auxiliary parameters (θ^a), i.e., parameters of the auxiliary model, when estimated using actual data versus simulated data, are very close

[38] Ideally, we would want to capture the heterogeneity between all states of India and estimate different parameters for each state as that is the administrative level at which many policies are formulated. However, we do not have enough data, especially in states where manufacturing is not a large part of the economy, to credibly estimate model parameters at this level of disaggregation.

to each other.

Implementing such a procedure for our model is challenging for two reasons. First, estimating auxiliary parameters related to firm dynamics is very computationally intensive since this involves repeatedly solving the Bellman equation and the policy functions. Thus, this brute-force approach would be extremely slow and costly. Second, in our setup, firms face discrete (active, dormant, exit) and continuous choices (how much labor and capital to employ). In such an environment, small changes in parameters, like the fixed production costs, could result in discrete changes in the simulated data. A fall in fixed production costs could result in a lot of firms choosing not to become dormant, and discrete changes in the simulated data. This would preclude us from using gradient-based optimization methods, further slowing estimation. Therefore, to estimate the model parameters, we adopt the strategy proposed by Golombek and Raknerud (2018), which utilizes the smoothing properties of the conditional expectations operator.

To address these challenges, we specify an auxiliary model with the same parameters as the true parameters in the structural model. We then derive a likelihood function to estimate the auxiliary parameters (we need not worry about any biases in the estimation, as we will be constructing the same, possibly biased, moments from the simulated data). In econometrics parlance, we perform maximum quasi-likelihood estimation (Q-MLE).

Had we taken a brute force approach, we would have generated data from the model for some structural parameter values $\hat{\theta}$. We would then re-do the Q-MLE using these simulated data to get another estimate of $\hat{\theta}^a$ and keep going until the $\hat{\theta}^a$ from the simulated data is the same as the $\hat{\theta}^a$ from the actual data. However, this would involve a large computational burden as estimating the Q-ML function over and over again is time-consuming.

Instead, we take an approach that is much less computationally demanding. Our approach has two key steps. First, we estimate the parameters of the auxiliary model from the data just once and get $\hat{\theta}^a$. We use a score condition (i.e., the sum of the squares of derivatives of the quasi-likelihood function), which is zero at the estimated $\hat{\theta}^a$. Call this score function, which depends on θ^a and the data, $S(\theta^a, data)$ and this is zero at $\hat{\theta}^a$. Next, we choose $\hat{\theta}$ for the structural model, simulate data, and find $\hat{\theta}$ which brings the score condition with the simulated data as close to zero as possible.

In other words, instead of matching moments or parameters, we set the objective to find structural parameters ($\hat{\theta}$) of our model such that the score function is also satisfied with simulated data at the estimated auxiliary parameters ($\hat{\theta}^a$). Intuitively, this is when the simulated data is very close to the actual data, but we don't have to re-estimate the auxiliary model in each search iteration.

There remains the problem that, because exiting, dormancy, and production are binary choices, the score function can be jagged as it can change a lot for small changes in θ. We deal with this by simulating the firm trajectories from the structural model to get the probability of these binary choices, which are continuous in θ, and use these in the score condition rather than the binary choices. The probabilities are essentially the conditional expectations of the binary decisions and hence smooth.

6.1.1 Parameter Partitions and the Auxiliary Models

As described above in section 6.1, we begin by estimating the auxiliary parameters corresponding to the structural parameters. Even though we have to estimate the auxiliary models only once, this is still computationally intensive as each iteration of the optimization algorithm requires resolving the Bellman equation and the policy functions. Following Golombek and Raknerud (2018), we partition the set of θ parameters that we estimate into three sets. The parameters that govern (a) the firm's static choices including prices and intermediate inputs, (b) the decision to produce or be dormant within each period, and (c) the dynamic decisions of the firm, e.g., labor and capital, and the decision to exit or stay. It is the third set of parameters that is computationally most intensive to estimate, and reducing that set is efficient. We estimate the quasi-likelihood function for each set of parameters as follows. For specific details, see Appendix D; here, we present a brief overview.

Parameter Group 1: $\theta_1 = \{\tilde{\gamma}_0, \tilde{\gamma}_1, \sigma_\gamma^\varepsilon\}$

Note from equations (5) and (6) that if we treat current and past choices of firms about labor and capital as exogenous, then the likelihood of observing a certain value added in the data depends only on θ_1 and calibrated parameters. This likelihood function assumes that labor and capital are exogenous and violate the structural model, and hence is a quasi-likelihood function rather than a component of the likelihood function. It allows us to estimate θ_1^a.

Parameter Group 2: $\theta_2 = \{\mu_f^{PP}, \mu_f^{DP}, \sigma_P\}$

These parameters govern only the firm's choice to produce or be dormant. This choice is made after labor, capital, and fixed cost shocks have occurred, and subsequent factor payments do not depend on it. From equation (5) and given $\hat{\theta}_1^a$ from Step 1, we can construct an approximation of $\tilde{\phi}_{it}$ as $\hat{\tilde{\phi}}_{it} = \frac{VA_{it}}{L_{i,t}^{\alpha_L} K_{i,t}^{\alpha_K}}$. The quasi log-likelihood function of θ_2 is constructed based on whether the firms find it profitable to produce or not, after paying the fixed production cost. Strictly speaking, the choice of production or dormancy also affects firms' future value functions through the hysteresis of production cost. To reduce the computational burden, we ignore the hysteresis of the production cost when we construct the quasi-likelihood function for θ_2. Therefore, the quasi-log-likelihood function of θ_2 reflects the probabilities of producing and being dormant.

Parameter Group 3: $\theta_3 = \{c_{Hc}, c_{Fc}, c_{Hr}, c_{Fr}^L, c_{Fr}^S, c_{HK}, c_{FK}, \sigma_{Lc}^\varepsilon, \sigma_{Lr}^\varepsilon, \sigma_K^\varepsilon, c_{FK}^E, \mu_f^E, \sigma_E\}$

These remaining 13 parameters pertain to various adjustment costs, shocks to inputs, and scrap values. They govern the firms' dynamic choices and can be estimated using a likelihood function for observing the values of labor, capital, and exit choices that we see in the data. This step is computationally the most demanding part of our estimation procedure as it requires re-estimating the value function for each trial value of θ_3^a.

6.1.2 Indirect Inference

We show in the appendix that the partial quasi-likelihood estimator $\hat{\theta}^a = \left(\hat{\theta}_1^a, \hat{\theta}_2^a, \hat{\theta}_3^a\right)$ satisfies a score moment condition which is the derivative of the sum of the three quasi-likelihood functions above with respect to θ^a. The final step for us is to simulate smooth trajectories of firms for a given value of the structural parameter vector θ. We take the data of the first year of each firm as given, and simulate smooth trajectories of each firm until 2018, which is the last year of data we use. We will use the same sample period to construct the score moment condition for the structural parameter vector θ. The indirect inference estimator $\hat{\theta}$, is that value of θ such that the simulated data from the model yields the lowest value of the score moment condition at $\hat{\theta}^a$.

6.1.3 Incorporating Missing Data into the Estimation

There is a further problem, namely that we have holes (missing data) in the Annual Survey of Industries data. The dataset is a census only for firms with over 100 workers, so small firms need not be sampled each year. Further, firms may be missing from the data if they do not comply with the survey, which is often the case.

If we do not deal with the missing data issue, the holes in the data will affect our estimation. First, in the estimation of the auxiliary model, we will miscalculate the transition of firms' status from production/dormancy to exit, as we will have trouble identifying if firms that are disappearing from the data are truly exiting or not because of these missing data issues. Second, in the second step of the indirect inference procedure, the simulated firm trajectories will not match the actual data. For example, the probability of firms exiting in the simulated data without accounting for the missing probabilities will be lower than that in the actual data.

To deal with such gaps in the data, we adapt the simulation procedure to mimic missing patterns in the real data. We first use actual data to estimate the probability that data will be missing, conditional on employment, capital, production status, industry, state, and year.[39] For example, if there is a hole in the data for a firm, we would look at whether it reappeared later. If it did, that hole would be because it was missing. If the firm does not reappear, it could either be missing or it could have exited. The longer the time period of data we have in the future, the more confident we are that the hole in this event is because a firm has exited. From this information and the assumption of independence between being missing and exiting, we can back out the probability of exit.[40] In the second step of the indirect inference procedure (i.e., simulating the data), we use the estimated missing probabilities to drop data from the simulated dataset such that it mimics the pattern of holes in the actual data.

6.1.4 Identification

We now discuss the intuition behind the identification of the key parameters in the model. These are the means and variances of the fixed production cost shocks $\left(\mu_f^{PP}, \mu_f^{DP}, \sigma_P^2\right)$[41], and the parameters governing the scrap value distribution $\left(\mu_f^{E}, \sigma_E^2\right)$.

Recall that firms need to pay fixed costs to produce and can avoid them by going dormant. Thus, the probability of production given state variables, i.e., productivity and labor employment, helps identify the

[39]This can be made as flexible as desired. For example, we assume the polynomial function form of capital and employment when estimating the missing probability. It can be made conditional on the number of years of dormancy in the past or another variable that might matter.

[40]The probability that the firm has not reappeared (which is data) is the probability it exited in the first period, plus the probability it was missing (which we know) in the first period and exited in the second, .. plus the probability it was missing for the entire data set. With our assumption of independence, this gives us one equation in one unknown, the probability of having exited, which we can solve for.

[41]Note that the μ's and σ^2 are not the means and variances. The distributions are log-normal so that the log of the variable has this mean and variance

production cost shock parameters. In particular, the $\mu_f^{\cdot P}$'s adjusts to match the average probability of production across firms, and σ_P^2 will adjust to match the range of productive firms that end up producing in the data.

The intuition is the following. A higher $\mu_f^{\cdot P}$ increases the probability of relatively larger shocks, thereby reducing the average probability of production. On the other hand, an increase in σ_P^2 increases the likelihood of both small and large draws.Ceteris paribus, this will broaden the spectrum of productivity levels among firms choosing to produce, as some low-productivity firms get lucky and draw low-cost shocks.

Similarly, a higher average exit rate among firms will be consistent with a higher mean of the scrap value distribution, μ_f^E. Conditional on the exit rate, the broader the productivity spectrum of the exiting firms, the higher σ_E^2 has to be. Hypothetically, if all firms got the same scrap value $\left(\sigma_E^2 = 0\right)$, all firms below a threshold productivity would exit. If the average exit rate does not change, the only reason why some productive firms would exit and some relatively unproductive firms would stay is that the variance of the shocks is higher.

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 ($\sigma_{Lc}^{\varepsilon}$, $\sigma_{Lr}^{\varepsilon}$). Similarly, the transition of capital over time identifies capital adjustment costs and capital shocks. The mean and transition matrix of productivity $\tilde{\phi}_{ft}$ helps us identify the parameters governing productivity evolution $\tilde{\gamma}_0$, $\tilde{\gamma}_1$, $\sigma_{\tilde{\gamma}}^{\varepsilon}$. Note that we allow firing costs of capital to be different for exiting firms, and we find that the adjustment cost of capital is lower when firms want to exit. This makes sense as in the data, firms rarely downsize capital such as buildings and land when they stay in the market.[42]

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 Estimates of Structural Parameters

In this section, we report and discuss the magnitudes of our parameter estimates. Let's begin with the 9 parameters that we calibrate. These are reported in Table 3. The factor shares (α's), and the wages are based on simple averages of the corresponding numbers in the ASI data. The wage of non-regular workers is higher than that of regular workers because this includes contract workers and managers.[43]

We set the discount factor and the capital depreciation rate to 0.9. Discount factors are notoriously hard to estimate, and we choose this number as interest rates in India were around 7-9% in the period we consider. The demand elasticity is set to 3.94, which is the median value reported in De Loecker et al. (2016).

[42] Allowing for this also lets us better match the transition matrix in the data to that in the simulated data. Not allowing for it would bias the estimates of the transition to dormancy, especially for firms with a lot of capital.

[43] Contract workers make 37,000 rupees per month on average in high-performance states and 34,000 in low-performance states. This is what the firms pay for them, so that the worker would get even less, given that 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 high-performance states and 141,000 in low-performance states.

Table 3: Calibrated Parameters

Panel 1: Common		Panel 2: Labor and Capital Intensive Sectors			Panel 3: High- and Low-performance States		
			Labor	Capital		HP States	LP States
δ^V	0.9						
δ^K	0.9	α_I	0.67	0.75	w_r (1000 rupees)	45	39
σ	3.94	α_K	0.25	0.21	w_c (1000 rupees)	120	108
		α_{Lr}	0.66	0.57			
		α_{Lc}	0.34	0.43			

The structurally estimated parameters are reported in Table 4. We estimate a high degree of persistence in the profitability process, $\tilde{\gamma}_1 = 0.9$. So, a firm with very low profitability should expect to be in that state in the future. Hence, the only reason for such a firm not to exit would be exit costs. The parameters on fixed costs of production from panel 2 suggest that restarting production after dormancy is, on average, harder than continuing to produce. In fact, $\mu_f^{PP} < \mu_f^{DP}$ implies that there are significant advantages to keeping the plant active. In hypothetical simulations based on these parameters, we find that firms pay about 1.59% of their annual value added in fixed production costs. Estimates on hiring and firing costs are reported in Panels 4 and 5. A few things to note. First, hiring is easier than firing any type of worker. Second, hiring non-regular workers is easier than hiring regular workers. The average firm pays 71.3% vs 146.7% of the annual wage to hire a non-regular worker vs. a regular worker. This is consistent with the reality that hiring contract workers involves less paperwork and fewer formalities, and is usually done via a third party. Third, firing regular workers is much harder than firing contract workers. The costs are 4.7-7.4 times as much. Fourth, firing regular workers is harder in low-performance states than high-performance states and harder in larger firms than smaller firms. These estimates are consistent with the literature (e.g. Besley and Burgess, 2004; Chaurey, 2015) and with the empirical evidence we report in Section 4. In terms of quantitative magnitudes, these estimates correspond to the average firm in high- and low-performance states bearing 85% and 91%, respectively, of the annual wage in their region to fire a non-regular worker. The analogous firing cost of regular workers is 256% and 358% in the two regions. Finally, the exit cost parameters in panel 7 suggest that the net scrap value, $\tilde{f}^E$, defined in equation (13) is very low. In fact, it is negative for most firms, implying that, on average, firms must "pay" to exit. We find that in high-performance states, this is about 110.6% and 173.4% of average annual sales in high- and low-performance states, respectively.

7 Counterfactual Exercises

Our quantified model allows us to look at the effects of various policies on outcomes of interest like productivity, value-added, firm entry, employment, and the price index in manufacturing, or aggregate welfare (which corresponds to real income) in the economy. All counterfactuals are performed in steady state. We group firms into four industry×state categories for the counterfactual exercises: labor- and non-labor-intensive industries in high-performance and low-performance states. In this section, we look at the effects in partial equilibrium. We assume that total income and the price index are fixed. This does not allow for feedback effects via these channels which we allow for in Section 8.

Table 4: Parameter Estimates

<table>
<tr><th></th><th>HP</th><th>LP</th><th></th><th>HP</th><th>LP</th></tr>
<tr><td colspan="3">Panel 1: Profitability Process</td><td colspan="3">Panel 5: Adjustment Cost of Non-regular Workers</td></tr>
<tr><td>$\tilde{\gamma}_0$</td><td>0.189 (0.0043)</td><td>0.184 (0.0033)</td><td>c_{Hc}</td><td colspan="2">29.443 (0.8774)</td></tr>
<tr><td>$\tilde{\gamma}_1$</td><td colspan="2">0.89 (0.001)</td><td>c_{Fc}</td><td>36.18 (17.95)</td><td>34.71 (3.72)</td></tr>
<tr><td>$\sigma_\gamma^\varepsilon$</td><td colspan="2">0.71 (0.000478)</td><td colspan="3">Panel 6: Shocks to Factor Employment</td></tr>
<tr><td colspan="3">Panel 2: Fixed Production Cost</td><td>σ_K^ε</td><td colspan="2">0.38 (0.015)</td></tr>
<tr><td>μ_f^{PP}</td><td colspan="2">-21.07 (0.5460)</td><td>σ_{Lr}^ε</td><td colspan="2">0.38 (0.0125)</td></tr>
<tr><td>μ_f^{DP}</td><td colspan="2">20.55 (0.3781)</td><td>σ_{Lc}^ε</td><td colspan="2">0.68 (0.0138)</td></tr>
<tr><td>σ_P</td><td colspan="2">15.41 (0.3342)</td><td colspan="3">Panel 7: Exit Costs</td></tr>
<tr><td colspan="3">Panel 3: Adjustment Cost of Capital</td><td>c_{FK}^E</td><td colspan="2">146.88 (57.67)</td></tr>
<tr><td>c_{HK}</td><td colspan="2">237.40 (47.74)</td><td>μ_f^E</td><td>-402.64 (54.65)</td><td>-631.22 (108.58)</td></tr>
<tr><td>c_{FK}</td><td colspan="2">1663.17 (286.04)</td><td>σ_E</td><td colspan="2">528.50 (60.50)</td></tr>
<tr><td colspan="3">Panel 4: Adjustment Cost of Regular Workers</td><td></td><td></td><td></td></tr>
<tr><td>c_{Hr}</td><td colspan="2">94.79 (16.28)</td><td></td><td></td><td></td></tr>
<tr><td>c_{Fr}^L</td><td>222.25 (44.49)</td><td>257.68 (120.63)</td><td></td><td></td><td></td></tr>
<tr><td>c_{Fr}^S</td><td>171.61 (24.92)</td><td>210.74 (52.75)</td><td></td><td></td><td></td></tr>
</table>

Notes: Analytical standard errors reported in paranthesis.

In Section 7.1, we assume that capital is in fixed supply and consider two policy instruments that would facilitate firm exit: (a) a reduction in labor adjustment costs and (b) reductions in direct exit costs (i.e., increases in the scrap value). We use our policy instruments one at a time to match the average exit rates in steady state in each of the four groups to 4.5%.[44]

In Section 7.2, we allow for an upward sloping supply of capital. In Section 7.3, we show that there are synergies between the two policy instruments so that the combined effects of the two policies exceed the sum of their individual effects. In Section 7.4, we look at the cost efficacy of entry and exit policies. We compare the effects of using a fixed budget to reduce entry vs. exit costs. Most governments make great efforts to design policies that lower entry costs to attract firms. We show that there is a tradeoff: entry subsidies are better for employment while exit subsidies are better for value added.

Our counterfactuals have an important qualitative insight that is very relevant in terms of policy. We'll see that a reduction in firing costs alone in an economy where capital supply is relatively inelastic could easily reduce net employment, even though aggregate value added goes up. In such an economy, therefore, labor laws do indeed protect jobs if that is the aim. However, if labor firing costs are reduced after direct exit costs, i.e., scrap value is raised, the synergies between the two mitigate, and often undo, the reduction in net employment from reducing firing costs. This suggests that the path of reform is critical if politically sensitive employment losses are to be avoided. These results are not surprising given that we are in a second-best world with multiple distortions.

[44]This corresponds to 50% of the average exit rate among manufacturing firms in the US, which is 9%.

7.1 Matching U.S. Firm Exit Rate

We begin the counterfactual analysis by adjusting our policy instruments to attain 50% of the US firm exit rate, i.e., 4.5%.[45] To begin with, we'll assume that the total capital available is fixed. This is extremely conservative but serves as a good starting benchmark. We perform the counterfactual simulations separately for each of the four industry×state categories, i.e., we change the relevant policy instrument such that the exit rate for each category equals 4.5%, and then aggregate them. Since the baseline exit rates are different for each industry×state category, the policy has to be changed by a different amount to achieve the same exit rate for all categories. Results are reported in Table 5.

Table 5: Partial Equilibrium Counterfactuals – Target Exit Rate 4.5%

	Policy Instrument	Category	Baseline Exit Rate	Δ Value Added (%)	Δ Productivity (%)			Δ Employment (%)	Δ Mass of Firms (%)	Dormancy Length (Δ years)	Age (Δ years)	Δ million rupees or Δ %
					Aggregate	Entrants	Exiters					
1	Exit Cost	LI / HP	2.98	15.54	5.95	-2.32	7.43	9.21	20.57	-0.88	-4.60	+292.03
2		LI / LP	2.23	18.19	9.39	-3.71	10.72	-0.59	14.95	-1.53	-7.69	+457.74
3		CI / HP	4.46	0.54	0.11	-0.06	0.18	0.25	0.58	-0.02	-0.08	+4.74
4		CI / LP	3.32	17.91	2.93	-2.29	6.37	8.35	21.07	-3.65	-3.25	+168.74
5		Weighted Average	3.45	10.98	3.92	-1.71	5.17	4.62	12.87	-1.07	-3.23	
6		Aggregate India	3.45	14.27	3.23	-1.73	5.54	8.08	17.98	-1.09	-2.87	
7	Labor Adj Cost	LI / HP	2.98	22.19	6.50	-1.53	7.02	-18.01	30.81	-0.81	-4.10	-89.30%
8		LI / LP	2.23	21.62	7.10	-2.00	11.34	-33.08	24.31	-1.11	-5.43	-98.94%
9		CI / HP	4.46	0.49	0.08	-0.04	0.17	-0.51	0.51	-0.02	-0.08	-1.99%
10		CI / LP	3.32	18.10	2.93	-1.67	7.64	-20.37	20.13	-3.65	-3.15	-59.18%
11		Weighted Average	3.45	13.89	3.80	-1.09	5.29	-14.24	17.73	-0.99	-2.73	
12		Aggregate India	3.45	16.38	3.85	-1.25	5.51	-14.56	19.81	-1.09	-2.86	

Note: This table presents counterfactual estimates of various aggregate outcomes like value added, productivity, employment, etc. that result from changing one of two policy instruments: exit costs (rows 1-6) or labor adjustment costs (rows 7-12). The data is divided into four state-industry groups as mentioned in rows 1-4 and 7-10. For each group separately, we estimate counterfactual outcomes if the relevant policy is changed such that the exit rate for that group becomes 4.5%. As the status-quo exit rates are different for each group, the exit costs or labor adjustment costs are also changed by different amounts to achieve a common exit rate across groups. These results are reported in rows 1-4 and 7-10. Here, LP: Low-performance States, HP: High-performance states, LI: Labor-Intensive Industries, CI: Capital-Intensive Industries. The weighted average row (row 5 or 11), is an average of the four groups, where the weights correspond to the shares of firms in each group. In the Aggregate India row (row 6 or 12), rather than targeting a common exit rate for each group, we ensure that the policy is changed by the same magnitude to achieve an average exit rate of 4.5% across groups. This corresponds to results plotted in Figure 6.

7.1.1 Changing the Scrap Value: Average Effects

The first policy instrument we study is raising the mean of the scrap value distribution. The real-world analog would be policies that make courts more efficient and have a well-laid-out path to bankruptcy. What might we expect? An increase in the mean scrap value results in more firms getting high enough scrap value draws to warrant exit. Low-productivity firms that do not have very high employment (since firing costs have not fallen) are naturally more affected by this. The increase in scrap value works to raise the average productivity of exiters, as well as productivity overall, and to reduce employment as the number of exiting firms rises. It also encourages entry, as the present value of entry rises, and makes selection less strict, making the average entering firm less productive. This force works to reduce average productivity overall. As the mass of firms increases, and as average productivity rises, so does value added. Employment could go either way. It would rise because the mass of firms rises and because selection among entrants weakens, but it would fall due to firms exiting. Dormancy falls, as does the average age of firms.

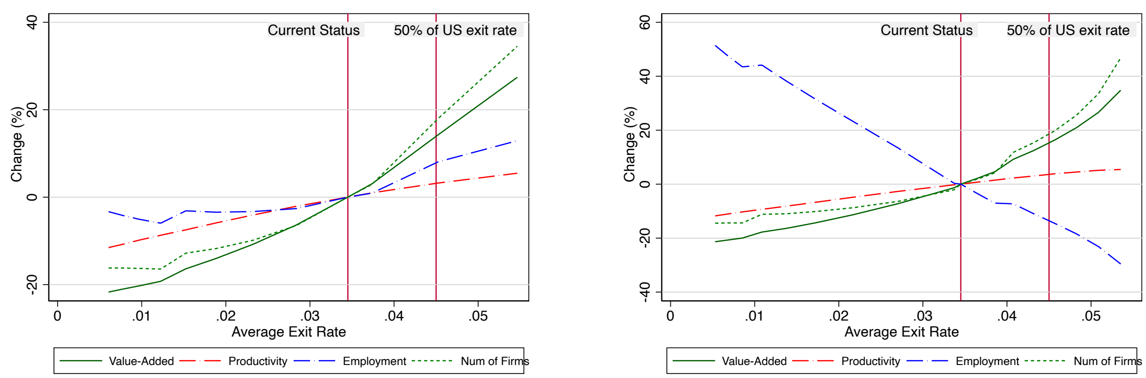
As stated earlier, we perform the counterfactual simulations for each of the four categories[46] separately. That is, we raise the mean of the scrap value distribution such that the average exit rate for each category

[45]Even if we make labor firing costs zero, we cannot match the US firm exit rate. First, this shows that frictions other than labor adjustment stall firm exit in India. Second, this is also why we chose 50% of the US firm exit rate as the target.

[46]Labor-intensive in high-performance states, labor-intensive in low-performing states, capital-intensive in high-performance states, and capital-intensive in low-performing states

equals 50% of the U.S. exit rate, i.e., 4.5%. The counterfactual results for each category are reported in rows 1-4 of Table 5. To estimate national effects, we compute a weighted average of the relevant outcome (like value added or employment), where the weights correspond to the shares of firms in each group in the pooled data between 1999–2008. These results are reported in the fifth row.

As a result of this policy change, the average value added and firm mass in manufacturingincrease by 10.98% and 12.87%, respectively. Employment rises by 4.62%.[47] Productivity rises by 3.92%. There is selection among entrants and exiters as scrap value increases. With the reduction in exit costs, firms with moderately higher productivity levels, who previously remained in operation, now also opt to exit the market, raising the average productivity among incumbents. Since lower exit costs also imply reduced entry barriers, the market sees an influx of new entrants with lower productivity levels than before, thereby reducing the average productivity of firms. The former effect dominates so that average productivity rises.[48] And the average time firms spend in dormancy goes down by 1.07 years.



(a) Effects of changing scrap value

(b) Effects of changing labor adjustment cost

Figure 6: Partial Equilibrium Counterfactual Exercises with Fixed Capital

Notes: Note that both panels have different y-axis ranges. The figures plot the counterfactual outcomes (value-added, productivity, employment, and mass of firms) as a result of changing policy. The relevant policy is changed by the same magnitude for each of the four industry×state categories to attain a target average exit rate. The figure plots the counterfactual average exit rates on the x-axis, while the corresponding outcomes are on the y-axis. To obtain average outcomes or exit rates, each of the four categories is weighted by the mass of the firms in the pooled data. The results corresponding to attaining 50% U.S. exit rate are also reported "Aggregate India" row of Table 5.

We present results graphically in Figure 6, noting that the estimates are generated using a slightly different approach. Rather than targeting a uniform exit rate across each industry×state category, we vary the policy parameter—specifically, the mean scrap value—by an identical amount across all categories, such that the weighted average exit rate matches a target level (e.g., 4.5%). The x-axis plots the resulting counterfactual exit rates generated through this uniform policy shift, while the y-axis depicts the corresponding percentage changes in firms' value-added, productivity, employment, and mass. We use this variation for the figures since, by construction, there is no change in any of the outcome variables at the status quo exit rate. For comparison, we report the counterfactual estimates using this approach with a targeted average exit rate of 4.5% in the "Aggregate India" row of Table 5. The two methods yield

[47]We explore the heterogeneity in state groups and industry that drives this fall in Section 7.1.3

[48]The avg. productivity among firms that exit increases by 5.17% while it falls by about 1.71% among entrants.

similar, but of course, different results.

7.1.2 Changing the Labor Adjustment Costs: Average Effects

The next policy we study is lowering labor firing costs to achieve the target exit rate. The real-world analog would be implementing labor reforms. These numbers are reported in rows 7–12 of Table 5 and plotted in Figure 6b. Quantitatively, the weighted average effects on value-added (13.89%), mass of firms (17.73%), and productivity (3.8%) are not very different from increasing the mean scrap value. As we had observed before, there is selection into entry and exit, with the selection effect into exit dominating and resulting in a higher average productivity.

The main difference is that when we reduce firing costs, employment in manufacturing falls by 14.24%. This is a key insight from our model. Employment falls because a different set of firms exit when we reduce firing costs, vs. when scrap value is increased. Reducing firing costs results in large, inefficient plants with many workers firing their workers and exiting. This releases a lot of labor, which is not fully absorbed by entering firms. Such firms would not have exited when scrap value alone fell, as the exit costs for them in terms of labor firing costs would prevent them from doing so. In part, this is because capital in our baseline economy is fixed. Had we made capital elastic, there would have been more entry, which would have mitigated the adverse employment effects of reducing firing costs. We explore the role of capital supply elasticity in Section 7.2 below.

7.1.3 Heterogeneities across State Group and Industries

The effects of facilitating firm exit vary significantly across states and industries, depending on their initial conditions (see rows 1–4 and 7–10 of Table 5). In capital-intensive industries located in HP states, exit rates are already close to the counterfactual target of 4.5% (i.e., 4.46%), leaving limited scope for additional adjustment. Consequently, the changes in outcome variables for this group are minimal. In contrast, labor-intensive industries in LP states exhibit substantial gains in value-added (18–22%) and productivity (7–9.4%) under both policy instruments. These effects are consistent with there being more significant pressure to exit on firms located in LP states. Similarly, the negative effects on employment of a reduction in labor adjustment costs are particularly pronounced in LP states (rows 8 and 10), as firing costs here are higher and the prevalence of low-productivity, labor-intensive firms is greater.

An increase in the mean scrap value leads to employment gains concentrated in the labor-intensive sector of HP states (row 1) and the capital-intensive sector of LP states (row 4). As labor adjustment costs remain unchanged, the exiting firms tend to be those with the lowest productivity rather than those with large labor forces. Consequently, fewer workers are displaced compared to a scenario involving a reduction of firing costs. It is worth noting that, somewhat surprisingly, employment falls in labor-intensive industries of LP states. As compared to the LI/HP and CI/LP groups, the mean scrap value has to be raised a lot more to reach the targeted exit rate. This has two implications. First, exiting firms release a lot more workers than for the other two categories. Second, the new entrants are small and quick to leave. Indeed, the average age of firms in this category now falls to 7.7 years, more than for any other category. Consequently, employment slightly falls, although value added rises considerably due to the increase in the mass of entering firms and the increase in productivity.[49]

Targeting the US firm exit rate may be unrealistic, especially for low-performing states with limited state capacity. However, it is helpful to know how much the low-performing states (like Bihar, Madhya Pradesh, and Uttar Pradesh) could gain if they could achieve the exit rates of the high-performing states (like Maharashtra and Tamil Nadu). Since some states in India have achieved these goals, they may be more reasonable targets for policymakers with an available roadmap to pursue. Our estimates suggest that if institutional reform could increase the scrap value in the LP states enough to match the exit rates of the HP states, then the value added and employment would increase by 11.6% and 4.0%, respectively. Relatedly, it is also important to note that the LP states can achieve much more significant gains in capital-intensive industries by achieving exit rates of the HP states than the HP states can achieve by targeting 50%

7.2 Elastic Capital Supply

All our counterfactual estimates are very sensitive to what we assume about the supply curve of capital. As reported in Table 6 and Table 7, higher elasticity of supply magnifies the effects considerably. Why? As we have seen, easing exit barriers in our baseline model can create net entry and value added. The effects on employment depend on the policy instrument that is used. In our baseline economy, firms have to work with a fixed amount of capital. Consequently, entry drives up the price of capital and chokes off further entry. If the supply elasticity of capital is positive, in contrast, an increase in entry raises the return to capital, which attracts more capital, which attracts more entry, and so on. Note first that scaling up capital does not affect aggregate productivity or that of entrants and exiters. Had we just doubled the availability of capital, it would have just doubled all the outcomes, leaving cutoffs unchanged. In other words, as wages are assumed fixed, there would be a pure scaling effect. Having elastic capital not only scales up the capital available but also raises the price of capital and, hence, its cost. However, it raises its resale value by the same amount. Thus, even adding increases in the price of capital does not affect cutoffs.[50] This is also why dormancy length and age are invariant to the elasticity.

Note, however, that value added, employment, and the mass of firms explode. As compared to keeping capital stock fixed, the increase in employment is 3-4 times as much when the capital supply elasticity is 0.5. In other words, even when we make the conservative assumption that a doubling of the return to capital only increases its supply by 50%, we get large effects. These counterfactuals are particularly encouraging in terms of how much labor could be absorbed by reducing exit costs coming from low scrap values, even if the price of capital rises in order to increase its supply.

When we look at the effect of reducing firing costs as capital becomes more and more elastic, we see a less rosy picture. Again, note that productivity, age, and the length of dormancy are unaffected by making capital elastic. As before, value added, employment, and the mass of firms are affected. Note that even with capital expanding, the employment effects of reducing firing costs remain stubbornly negative.

[49]Table C.4 in the Appendix C.1 gives the analogue of Table 5 for the Aggregate India case.

[50]We choose to model capital as we have done, rather than having a rental rate of capital and assuming firms rent the capital. Adjustment costs are at the heart of what we are doing, and it makes no sense to think of firms' capital decisions in this way. For example, firms build structures and acquire capital specifically tailored to their purposes. They cannot costlessly adjust them.

Table 6: Changing the Scrap Value as in the Base Counterfactual with Elastic Capital Supply

Elasticity (ε_K)	Category	Value Added (%)	Productivity (%) Aggregate	Entrants	Exiters	Employment (%)	Mass of Firms (%)	Dormancy Length (Δ years)	Age (Δ years)
0	Weighted Average	10.98	3.92	-1.71	5.17	4.62	12.87	-1.07	-3.23
0.1		12.55	3.92	-1.71	5.17	6.05	14.47	-1.07	-3.23
0.2		14.15	3.92	-1.71	5.17	7.50	16.10	-1.07	-3.23
0.5		19.18	3.92	-1.71	5.17	12.05	21.20	-1.07	-3.23
0.75		23.62	3.92	-1.71	5.17	16.08	25.72	-1.07	-3.23

Note: The weighted average is an average of the four groups, where the weights correspond to the shares of firms in each group.

Table 7: Changing Labor Adjustment Costs as in the Base Counterfactual with Elastic Capital Supply

Elasticity (ε_K)	Category	Value Added (%)	Productivity (%) Aggregate	Entrants	Exiters	Employment (%)	Mass of Firms (%)	Dormancy Length (Δ years)	Age (Δ years)
0	Weighted Average	13.89	3.80	-1.09	5.29	-14.24	17.73	-0.99	-2.73
0.1		16.20	3.80	-1.09	5.29	-12.76	20.14	-0.99	-2.73
0.2		18.58	3.80	-1.09	5.29	-11.23	22.63	-0.99	-2.73
0.5		26.13	3.80	-1.09	5.29	-6.38	30.53	-0.99	-2.73
0.75		32.95	3.80	-1.09	5.29	-2.01	37.66	-0.99	-2.73

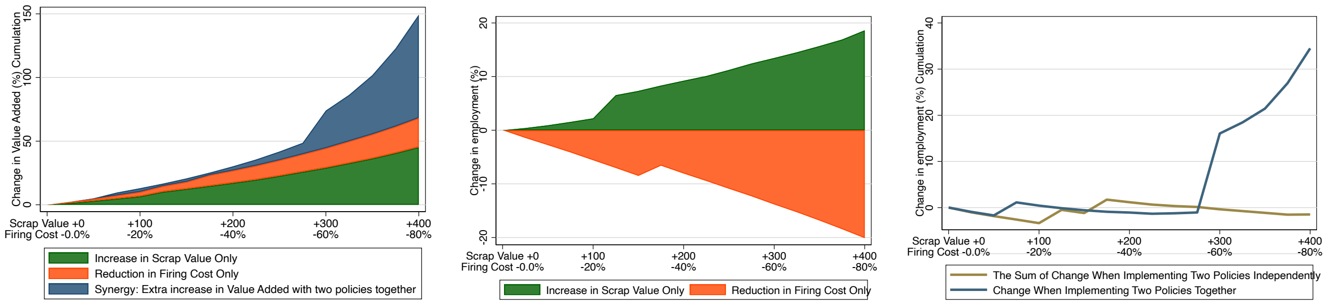
Note: The weighted average is that of the four groups, where the weights correspond to the shares of firms in each group.

They fall in absolute terms, from -14.24% to -2.01%. This is due to the same selection forces being in play. Having more capital scales up the system, but reducing firing costs still encourages low-productivity, labor-intensive firms to shed labor, and the increase in the mass of firms is not enough to overcome this, though if capital is elastic enough, ultimately employment would rise when firing costs fell. Value added and the mass of firms move in line with each other and less than double as elasticity rises to .5. In other words, even though employment is not positively affected, the economy grows, and the real income of workers rises. These counterfactuals are particularly discouraging in terms of how much labor could be absorbed by reducing exit costs coming from labor firing costs even when capital supply is not fixed.

7.3 Synergies in Labor Adjustment and Exit Costs

Figure 7a presents the quantitative estimates of the synergies between our two policy instruments on value-added. On the x-axis, we plot the different magnitudes of the policies, and the y-axis plots the corresponding change in value-added. At any scrap value or firing cost level, the height of the green and orange plots denotes the percentage change in value-added due to these policies, respectively, but implemented in isolation. For example, only increasing the mean of scrap value (μ_f^E) by 300 million rupees increases value added by 27.9%, and only reducing firing costs by 60% increases value-added by about 17.1%. The height of the blue plot gives us the "extra" increase in value-added if both the policies are implemented together; in the above example, the total value-added would go up by about 75%, so an excess of 30 percentage points.

Essentially, this occurs due to synergies between the two. To understand the intuition, consider the effect of an increase in scrap value. This alone shifts up the expected ex-ante profits for any given mass of firms. This, in turn, increases the point at which expected profits are zero and so fosters entry and increases the mass of firms. However, when scrap value is increased in the presence of lower firing costs, the shift in expected ex-ante profits is much higher as firms additionally benefit from less rigid labor markets. Firms now realize that their response to each policy in isolation is too little: after all, reducing firing costs shifts up the profits from entering as a function of the mass of firms, so even more firms would want to enter! This is what lies behind the synergy effects.



(a) Value Added (b) Emp. – Independent Policies (c) Emp. – Joint Policies

Figure 7: Synergies in Policies

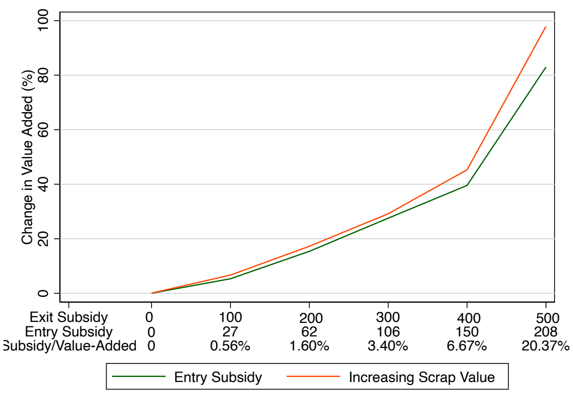
Also, note that the larger the magnitude of the policies implemented, the greater the synergies. We have depicted synergies between the two policies on value-added. We now perform the same exercise for employment. As the effect of reducing the firing costs of labor on employment is negative, we depict the effect in two parts. In Figure 7b, we depict the effect of raising scrap value alone in green and of reducing firing costs alone in orange. As the latter reduces employment, this curve lies below zero. In Figure 7c, we depict the sum of the two policies by the brown line. The gray curve gives the total effect when both policies are enacted simultaneously. Note that it lies above the brown one, i.e., there are synergies. Also note that when firing costs are reduced by about 60% and the mean of the scrap value distribution is increased by about 300 million rupees (or about 7.5 million dollars using the exchange rate of 40 Rs. per dollar), total employment actually increases. It rises swiftly after that. This highlights the importance of combining the reforms and doing them at scale. This is a consequence of there being multiple distortions at work in our setting.

7.4 Subsidies to Entry versus Subsidies to Exit

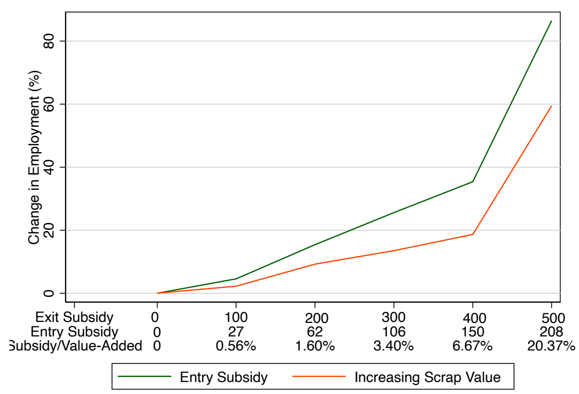
In this section, we compare the outcomes of targeting a reduction in entry costs versus an increase in scrap value when the same budget is available for both. In other words, we raise the mean scrap value (or reduce entry costs) till the budget is exhausted. This gives us an idea of how they compare in terms of "bang for the buck". In Figure 8 we put the percentage change in scrap value/entry costs corresponding to a budget that is a given fraction of GDP on the x axis. For example, a 100 million rupees increase in scrap value and a 27 million rupees fall in entry costs both exhaust a budget of .56% of India's GDP.

It is clear from Figure 8a that reducing exit costs has a much higher effect on value-added than reducing entry costs for a given budget, and more so for higher budgets. There are three forces at work. First, an increase in the mass of entrants raises value added by definition. Second, an increase in average productivity does the same. Third, the exit of firms removes low-productivity firms and frees up capital for use by more productive firms.

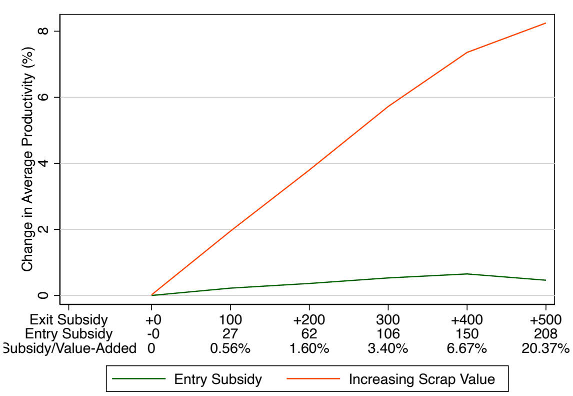
Both entry and exit subsidies increase the mass of entrants as ex-ante profits rise in both cases. However, with the entry subsidy, the average exit rate changes only a little, but with the exit subsidy, it changes a lot, as in Figure 8d. This is what makes the employment effects of an exit subsidy lower than those of an entry subsidy, as in Figure 8(b). Exit subsidies replace low-value-added, low-productivity exiters with entrants with a higher average productivity. This raises average productivity, as shown in Figure 8c. In contrast, entry subsidies make selection weaker, and this reduces the average quality of entrants without affecting the average productivity of exiters by much. Consequently, average productivity with entry subsidies changes by little and can even fall, as in Figure 8c. Finally, with exit subsidies, exiters release capital to be used by other firms, and this reallocation raises value added. This is what lies behind the value added rising by so much more with exit costs being reduced.



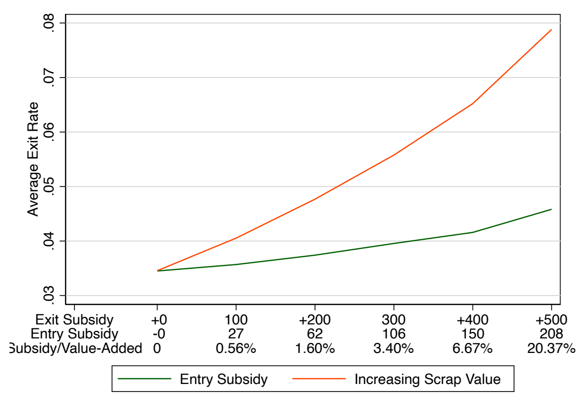
(a) Value Added



(b) Total Employment



(c) Average Productivity



(d) Exit Rate

Figure 8: Subsidies to Entrants vs Reduction in Exit Cost

8 General Equilibrium vs Partial Equilibrium

In this section, we generalize the model in two dimensions. First, we endogenize the price index and expenditure in a location. Second, we allow trade between HP and LP states. Thus, in the general equilibrium version, reducing exit barriers will have three additional effects. With an endogenous price index, entry gets choked off faster as the price index falls with entry, thereby reducing demand at any price. On the other hand, a higher income and a lower price index in the manufacturing sector leads to higher real income and expenditure, further incentivizing entry. Lastly, internal trade allows for spillover effects across the two groups of states. For example, if only HP states reform and their income rises, the demand for LP states' products will rise due to this. Firm's decisions as to where to enter will also be affected as the HP states real income, and hence demand for the product, will increase by more. Thus, there can be both positive and negative spillovers across the groups of states.[51]

8.1 Static Decisions in General Equilibrium

Firms engage in monopolistic competition and set a price at the factory door, which after including transport costs, if any, gives the price in the destination market. One price p is being set by a firm. This results in a different price paid by consumers in the two states due to transport costs. Firms at location l sell to location d with an iceberg transportation cost τ_{ld}.[52] $\tau_{ld} = 1$ if $l = d$ and $\tau_{ld} > 1$ if $l \neq d$. We assume that the utility function over the aggregate manufactured goods made in industry k[53], agriculture, and services is Cobb-Douglas so that the share of expenditure on the manufacturing sector k is a constant, β_k. Let $P_{k,d}$ be the aggregate price index for the manufactured good made in sector k, which is a CES aggregate of the prices of goods sourced from firms in different locations. E_d is the aggregate income at location d. This includes income from all sectors of the economy.[54] However, we assume that income from sectors other than manufacturing is fixed. The quantity demanded of the aggregate good made in sector k will therefore be $\beta_k E_d / P_{k,d}$. The demand for a variety of the manufactured good in sector k, made in location l, selling to location d will be the unit input requirement of a variety, $\frac{(p\tau_{ld})^{-\sigma}}{P_{k,d}^{-\sigma}}$, times the demand for the aggregate good in sector k. Hence,

$$D_{k,ld}(p) = (p\tau_{ld})^{-\sigma} \frac{\beta_k E_d}{P_{k,d}^{1-\sigma}}. \tag{15}$$

Since we assume that profits are dissipated to consumers as income, the total income from labor- and capital-intensive industries in the manufacturing sectors is equal to their value-added.In each period t, given labor L_{ct}, L_{rt}, and capital K_t, the firm in location l in industry k makes a static decision to maximize profits by choosing intermediate inputs and prices at location d, subject to the market for its good clearing.

$$\max_{I_t, p} \quad \sum_d (p\tau_{ld})^{1-\sigma} \frac{\beta_k E_d}{P_{k,d}^{1-\sigma}} - r_I I_t \qquad \text{s.t.} \qquad \sum_d p^{-\sigma} \tau_{ld}^{1-\sigma} \frac{\beta_k E_d}{P_{k,d}^{1-\sigma}} = \phi_t L_t^{\alpha_L} I_t^{\alpha_I} K_t^{\alpha_K}.$$

The profit-maximizing price charged by firms is a function of productivity ϕ_t, labor employment

[51] There are other important channels of adjustment that we don't consider here. For example, if we allow for non-homotheticity in preferences, then structural transformation can magnify the positive demand effect further. Our goal here is to be conservative and to provide lower bounds for our quantitative estimates in a general equilibrium environment.

[52] The locations are either high- or low-performance states.

[53] k = Labor- or Capital- intensive sectors.

[54] $E_d = I_d^A + I_d^S + I_d^{M,K} + I_d^{M,L}$, where I_d^k stands for income at location d in sector k = agriculture, services, capital and labor intensive manufacturing.

L_{ct}, L_{rt}, and capital K_t. Therefore, we can derive the aggregate price index as follows.

$$P_{k,d}^{1-\sigma} = \sum_l \int_{\Omega_{kl}} p_{kl}(\phi_t, L_{ct}, L_{rt}, K_t)^{1-\sigma} \tau_{ld}^{1-\sigma}$$

where Ω_{kl} is the set of all firms in industry k at location l. The per-period value-added of firms in industry k at location l is a function of L_{ct}, L_{rt}, and K_t. It takes the following form, and is similar to equation (5).

$$VA_{kl}(\phi_t, L_{c,t}, L_{r,t}, K_t) = \Gamma \left(\phi_t L_t^{\alpha_L} K_t^{\alpha_K}\right)^{\frac{\frac{\sigma-1}{\sigma}}{1-\alpha_I \frac{\sigma-1}{\sigma}}} \left(\sum_d \tau_{ld}^{1-\sigma} \frac{\beta_k E_d}{P_{k,d}^{1-\sigma}}\right)^{\frac{\frac{1}{\sigma}}{1-\alpha_I \frac{\sigma-1}{\sigma}}} \tag{16}$$

Here, $\Gamma = \left(1 - \alpha_I \frac{\sigma-1}{\sigma}\right) \left(\frac{1}{r_I} \alpha_I \frac{\sigma-1}{\sigma}\right)^{\frac{\alpha_I \frac{\sigma-1}{\sigma}}{1-\alpha_I \frac{\sigma-1}{\sigma}}}$ is a constant.The per-period value-added of firms is increasing in its productivity ϕ_t, labor employment $L_{c,t}$ and $L_{r,t}$, and capital K_t.

8.2 General Equilibrium Counterfactuals

For our counterfactual simulations in General Equilibrium, we assume a capital supply elasticity of 0.75 following Hall and Jorgenson (1967). We also set the iceberg trade cost to equal 2.[55]. The GE counterfactuals are performed using the methodology for the "Aggregate India" row of Table 5. i.e., we change the policy by the same magnitude for all four industry×state categories rather than targeting a common exit rate. The key difference is that now there will be a common free-entry condition.

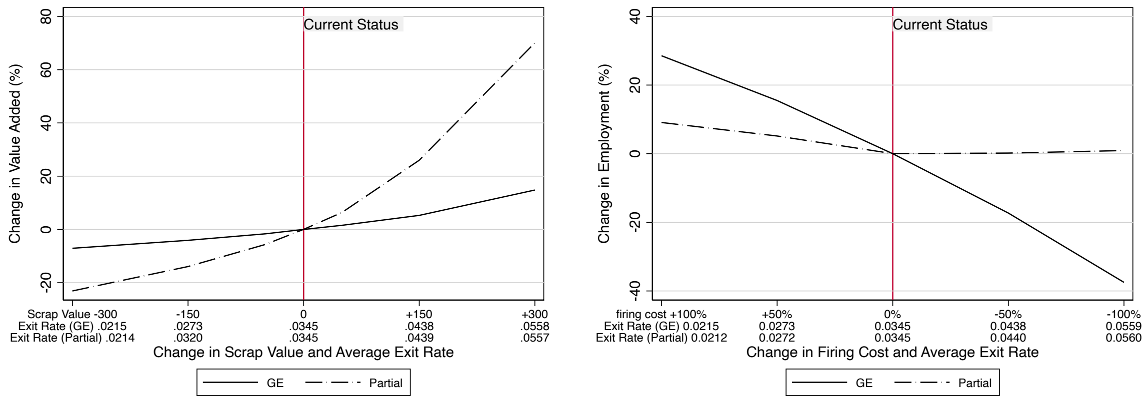
We illustrate this using two cases in Figure 9, and relegate others to Appendix C.3. As previously, the x-axis has the change in the policy and the the y-axis plots the percentage change in the variable of interest coming from the policy change. The dashed line plots the effects in partial equilibrium (PE), and the solid line corresponds to the counterfactual changes in GE.

Figure 9a presents the percentage change in value-added in *manufacturing* in GE and PE when we increase the scrap value (and corresponds to Panel (a) in Figure C.13, where we present additional results when scrap value changes). Panel (b) gives the percentage change in *manufacturing* employment when labor adjustment costs are changed. It corresponds to Panel (b) in Figure C.14. An increase in the mean of the scrap value distribution by 150 million rupees in all states results in a 26% increase in manufacturing value-added in partial equilibrium but only of 5.28% in GE. The employment effects of the exact same policy change in PE are 20% vs around zero in GE (see Panel (b) in Figure C.13). Similarly, in Figure 9b, there is actually a reduction in net employment if labor adjustment costs are reduced in all states in GE, while employment is roughly flat in PE .

Note that in general, the effects of reducing either kind of exit cost are more muted in general equilibrium (GE). With an endogenous price index, entry in manufacturing gets choked off sooner due to greater competition.[56] This negative GE effect of the price index overwhelms the positive force in GE of increased expenditure on manufacturing goods because the share of the manufacturing sector is small:

[55]During our study period, 1998-2018, India had state-specific value-added taxes, so cross-state shipments frequently stalled at state borders. We use a relatively high trade cost to capture this cost. Estimates for manufacturing trade costs for imports and exports are 1.49 and 2.42, respectively in Van Leemput (2021).

[56]This competitive force is similar to what happens in standard models like Melitz (2003).

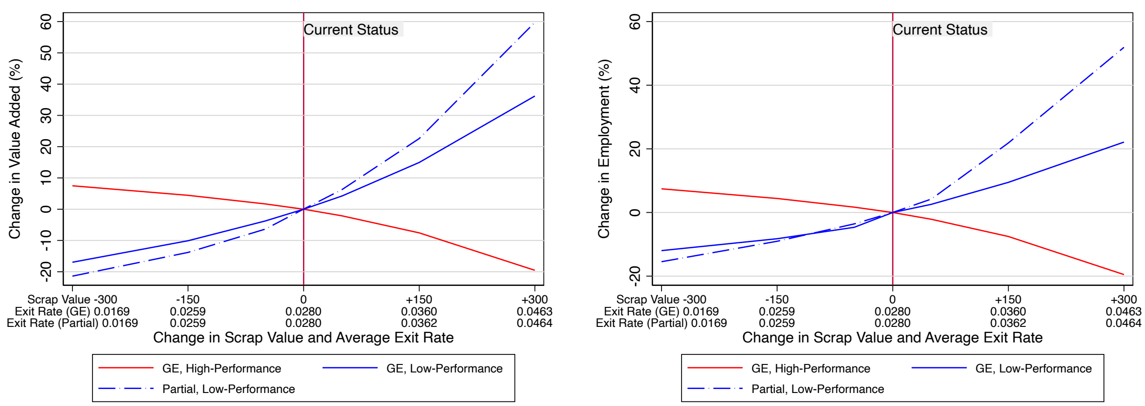


(a) Effects of changing scrap value

(b) Effects of changing labor adjustment costs

Figure 9: General vs. Partial Equilibrium Counterfactuals with capital supply elasticity 0.75

only 15% of GDP. Another consequence of the small manufacturing share is that percentage changes in *aggregate* welfare are lower than the percentage changes in value added in *manufacturing*.[57]



(a) Effects on Value Added

(b) Effects on Employment

Figure 10: GE Effects of changing scrap value only in LP states

There are considerable spillover effects if policies are changed only in one region. The region that reduces exit barriers attracts firms and increases value-added and employment, whereas the other region loses out. For example, increasing the scrap value by 150 million Rupees in the LP states increases the value added by 14.96% (Fig. 10a) and employment by 9.48% (Fig. 10b) in the LP states. However, both value-added and employment are reduced by 7.57% and 7.54%, respectively, in HP states. The negative spillover effects would be amplified if we also allowed for migration between regions in the model.

While we have incorporated elements of general equilibrium in this section, we have kept the output of Agriculture and Services fixed. Recent work on India finds that there are considerable spillovers across sectors, in particular to services (e.g., Fan et al., 2023). This would suggest that our estimated effects are

[57]Compare the three LHS and three RHS panels of Figure C.13 and C.14.

very conservative, as we do not allow for such interactions.

9 Conclusion

Governments often focus on policies to attract firms, boost employment, and enhance development. These include tax breaks and/or subsidies of various forms. Unfortunately, governments generally do not have a good track record of picking winners. Moreover, attempts to get multinationals to invest (by offering tax holidays or subsidies) often just enrich multinationals who then leave for better prospects elsewhere once the subsidies end, see (Bond, 1981). Or it can take the form of reducing real costs, which have real effects, as we do in this paper.

In this paper, we show that reducing exit barriers is at least as important as reducing entry barriers. Reducing exit barriers targets firms that should exit, but don't because of high exit costs, namely low productivity firms that face low scrap value/high firing costs. High exit costs lock productive resources with low-productivity firms, dragging down overall productivity. In addition, since exit costs also act as entry barriers, they deter entry, further slowing down growth. As shown in Section 7.4, spending the same amount on reducing exit barriers raises value added by more, productivity by much more, though it raises employment by less.

Exit costs are relevant for all economies, developed and developing. They are manifested primarily as bankruptcy costs in developed countries like the U.S. but in many 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."* However, there is little guidance in terms of identifying the importance of the various kinds of barriers we model, or whether there is heterogeneity in terms of this importance by industry type and/or region/states. Nor do they have any idea about what to avoid and what to embrace in terms of the timing of reforms.

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Supplemental Appendix

A Institutional History

Firms take a long time to exit in India. 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 varies 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.

A.1 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 Unions Act of 1926, and the Trade Disputes Act of 1929.

Since labor is a topic under the concurrent list[58] 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.[59] West Bengal has 31 acts,[60] and Telengana has 47. Over time, the IDA itself has been differentially 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 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 (it 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 one court per 500,000 workers, courts are heavily backlogged, and cases can take years to get resolved. 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

[58] 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 subjects allowing both the national parliament and the state legislatures to enact laws on these matters.

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

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

37% had been pending for more than 3 years.[61] Rao (2020) has shown that there is substantial variation across states in court efficiency. Hence, adjustment costs 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.

The biggest hurdle, however, comes from the uncertainty that firms face while making decisions. The court's interpretation of the laws has evolved. Sarkar (2019) documents that while many specific statutes have not greatly changed, the judiciary's interpretations of them have 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. Kaul (2020) 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 the protection of the IDA. For that, the court has to interpret what an "industry" is under the IDA. For example, are hospitals an industry, and 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? Do airline pilots and software engineers count as 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[62] case in 1960 that involved payment of retrenchment compensation to ward servants in JJ Hospitals, Mumbai. Initially, 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; hence, they are not an industry. The court framed a working principle that any systematic activity for the 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 hospital services were held to be material services, and hence, it was ruled that hospitals were, in fact, an "industry" under the IDA. However, the court contradicted itself seven years later in a 1967 case involving Safdurjung Hospital[63]. 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 people get treated. ... It cannot, therefore, be said to be an industry..." Similarly, in a 1963 case[64] In 1963, the court 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.[65] The Punjab National Bank shut down a particular branch office in 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 treasurer, appealed to the court, citing wrongful termination. In this case, the Supreme Court held that the treasurers and their nominees are servants of the bank and, thus, entitled to protection under the IDA.

The large country-made cigarette (beedi) industry in India employs a large army of non-regular workers who

[61] 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 (2006))

[62] AIR 1960 SC 610

[63] (1970) 1 SCC 735. Safdurjung Hospital v. Kuldeep Singh

[64] AIR 1963 SC 1873. University of Delhi v. Ram Nath.

[65] AIR 1955 SC 404

roll the cigarettes. Courts have differed in their judgment 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[66], the court ruled that although the workers were paid on a per-piece basis 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[67], 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 was not a "workman". However, this judgment 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, it established an employer-workman relationship. This was used later while adjudicating the Mohideen Sahib & Sons v. Industrial Tribunal, Madras[68] 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 that the workers were 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[69] the Supreme Court excluded workers not doing manual, clerical, supervisory or technical work from being "workmen". As against this, in a set of cases[70] 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.

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[66] AIR 1961 SC 644

[67] AIR 1962 SC 517

[68] AIR 1966 SC 370

[69] May & Baker (India) Ltd. v. Workmen. AIR 1967 SC 678; Western India Match Co. Ltd. v. Workmen (1964) 3 SCR 560; and Burmah Shell Oil Storage & Distribution Co. of India v. Burmah Shell Management Staff Association (1970) 3 SCC 378

[70] 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

A.2 Bankruptcy Laws

Unsurprisingly, bankruptcy laws, like labor laws. were 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 the Presidency Towns Insolvency Act of 1909 to deal with insolvency in the Presidency towns and the Provincial Insolvency Act of 1920 for other places. Bankruptcy proceedings for individuals, even today, are regulated under these 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 of 1985. Since the early 90s, governments have attempted various reforms with limited success. In 1993, for example, Debt Recovery Tribunals (DRTs) were set up. These were quasi-judicial institutions that streamlined the legal process and allowed speedy adjudication and swift execution of judgments (Visaria 2009). However, over time, the 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, over time, as courts have interpreted and reinterpreted the Act, its power has become diluted. For example, now the law permits borrowers to appeal - a measure that dilutes loan recovery. There has been a 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 and delaying the process. [71]

Another issue with SARFAESI is that there are 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 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 the 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 the 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

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

pro-debtor stance, and they are reluctant to order the liquidation of non-viable businesses (Ravi 2015; BLRC Report, 2015). Thus, even with SARFESI, large cases took an average of 6 years to resolve, and recovery rates averaged 26% – among the lowest in the world (Sengupta 2016). 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 proceedings. The IBC tried to replace overlapping provisions in 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 a trustee are appointed to take 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 minimal success due to several judicial bottlenecks and court congestion[72]. 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.

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Sengupta, R., Sharma, A., & Thomas, S. (2016). Evolution of the insolvency framework for non-financial firms in India. Working Paper.

[72]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]

B Additional Data Facts

B.1 Details about exit calculations

Measure	Data Source	Steps involved in calculation	Used in
All-India exit rate for formal manufacturing	ASI	1. Consider years 2001 and 2016. 2. Divide plants into cohorts (indexed by c) based on their age in 2001. 3. We compute the following from data. M_c^{2016}: mass of plants in cohort c in 2016. M_c^{2001}: mass of plants in cohort c in 2001. 4. Let δ_c be the annual exit rate for cohort c. We back out δ_c from the following relationship: $M_c^{2016} = (1-\delta_c)^{15} M_c^{2001}$ 5. All-India exit rate is then the weighted average of cohort-wise exit rates from step 4, with weights being the share of plants in each cohort as of 2001.	Fig 1a
All-India exit rate for informal manufacturing	NSS	We follow steps 1-5 outlined above for years 1994-95 and 2015-16. In step 4, we modify the formula to account for the 21-year gap between 1994-95 and 2015-16.	Fig 1b
Exit rates by age cohort for HP/LP states	ASI	For each state group (HP/LP states), we follow steps 1-4 outlined above.	Fig 3a

<table>
<tr><td>State-wise exit shares</td><td>ASI</td><td>Consider years 2001 and 2016.
Divide plants into cohorts (indexed by c) based on their age in 2001.
We compute the following from the data. M_c^{2016}: mass of plants in cohort c (all-India) in 2016. M_c^{2001}: mass of plants in cohort c (all-India) in 2001. M_{cs}^{2016}: mass of plants in cohort c for state s in 2016. M_{cs}^{2001}: mass of plants in cohort c for state s in 2001.
Let δ_{cs} be the annual exit share for cohort c from state s. We back out δ_{cs} from the following relationship: $\delta_{cs} = \frac{M_{cs}^{2001} - M_{cs}^{2016}}{M_c^{2001} - M_c^{2016}}$
State-wise exit share is then the weighted average of δ_{cs} from step 4 above, with weights being the share of plants in cohort c in state s.</td><td>Fig 2b</td></tr>
<tr><td>Firm-level exit</td><td>ASI</td><td>Using the sample from 1999-2018, we identify the last year each firm appears in the dataset. For firm i, let the last year be T_i.
Firm i is considered to have exited after year T_i if $T_i \leq 2007$. Since the dataset extends through 2018, this allows at least 10 years to confirm that the firm does not re-appear.</td><td>Fig 4a, Table 1</td></tr>
<tr><td>Firm-level exit</td><td>Prowess</td><td>Using the sample from 2000-2020, we identify the last year each firm appears in the dataset. For firm i, let the last year be T_i.
Firm i is considered to have exited after year T_i if $T_i \leq 2012$. Since the dataset extends through 2020, this allows at least 8 years to confirm that the firm does not reappear.</td><td>Fig 1b</td></tr>
</table>

B.2 Persistence of Entry Shares Over Time

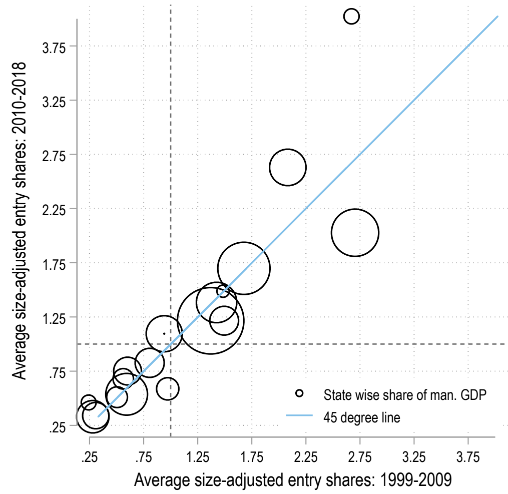


Figure B.1: Persistence of size-adjusted entry shares over time

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; the size of the circle is determined by the state-wise share of the overall manufacturing GDP. Entry shares line up very closely along the 45 degree line, indicating high persistence over time.

B.3 Details about Revenue Residuals

Suppose plant output follows $Y = \phi L^{\alpha_L} I^{\alpha_I} K^{\alpha_K}$, where ϕ is TFPQ, L is labor, K is capital, and I is intermediate inputs. Additionally, let plants face the demand function $D(p) = p^{-\sigma}E$, where p is plant-level price, σ is the elasticity parameter, and E includes aggregate expenditure and the aggregate price index.

The above production and demand functions imply that plant revenues are given by:

$$pY = E^{\frac{1}{\sigma}} \phi^{\frac{\sigma-1}{\sigma}} L^{\frac{\alpha_L(\sigma-1)}{\sigma}} I^{\frac{\alpha_I(\sigma-1)}{\sigma}} K^{\frac{\alpha_K(\sigma-1)}{\sigma}}$$

From here, revenue residuals are defined as:

$$\text{Revenue Residuals (RR)} = \frac{pY}{L^{\frac{\alpha_L(\sigma-1)}{\sigma}} I^{\frac{\alpha_I(\sigma-1)}{\sigma}} K^{\frac{\alpha_K(\sigma-1)}{\sigma}}} \tag{B.17}$$

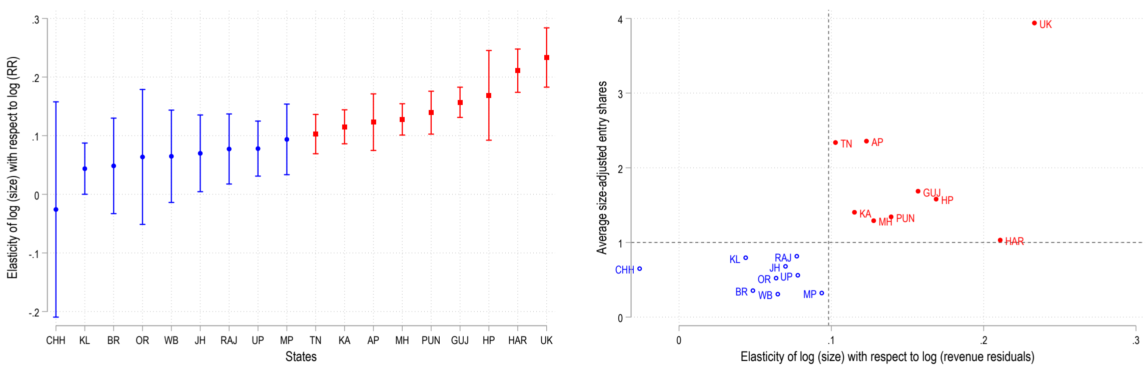
It must be noted that these revenue residuals are distinct from total factor revenue productivity (TFPR)[73]. Moreover, revenue residuals do not include plant-level prices. To see this, the above expression can be simplified as follows:

[73] Total factor revenue productivity, $TFPR = \frac{pY}{L^{\alpha_L} I^{\alpha_I} K^{\alpha_K}} = p\phi$.

$$
\begin{aligned}
\text{Revenue Residuals (RR)} &= \frac{pY}{L^{\frac{\alpha_L(\sigma-1)}{\sigma}} I^{\frac{\alpha_I(\sigma-1)}{\sigma}} K^{\frac{\alpha_K(\sigma-1)}{\sigma}}} \\
&= (p\phi)\left(L^{\alpha_L} I^{\alpha_I} K^{\alpha_K}\right)^{\frac{1}{\sigma}} \\
&= \frac{pE^{\frac{1}{\sigma}}\phi^{\frac{\sigma-1}{\sigma}}}{p} \\
&= E^{\frac{1}{\sigma}}\phi^{\frac{\sigma-1}{\sigma}}
\end{aligned}
$$

The second equality follows from the production function, whereas the third equality follows from the demand function. We use equation B.17 to compute revenue residuals, since we observe plant-level sales. We calibrate $\frac{\alpha_L(\sigma-1)}{\sigma}$, $\frac{\alpha_I(\sigma-1)}{\sigma}$, $\frac{\alpha_K(\sigma-1)}{\sigma}$ using the median factor expenditure on sales for each 2-digit industry.

B.4 Entry Shares versus Misallocation



(a) Misallocation Measures

(b) Entry Shares vs Misallocation

Figure B.2: Correlation between state-wise misallocation measures and entry shares

Notes: (1) We measure misallocation in each state using the elasticity of plant size – defined as the number of non-managerial workers – with respect to plant revenue residuals. Intuitively, plants with higher revenue residuals should have more workers, implying states with less misallocation should exhibit a higher elasticity between plant size and revenue residuals. The left panel shows estimates and 95% confidence intervals from a weighted regression of log(plant size) on log(plant revenue residuals) interacted with state fixed-effects. Specifically: (a) both log(size) and log(revenue residuals) are residualized by plant fixed-effects and 4-digit industry×year fixed-effects, and (b) the weight for state s, industry j in the regression is the ratio of sales of industry j in state s to total sales in state s.
(2) The right panel of the above figure shows the relationship between size-adjusted entry shares and misallocation measures. The figure shows that states with size-adjusted entry share below 1 have higher misallocation, and vice-versa.
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B.5 *Entry Shares versus Court Performance*

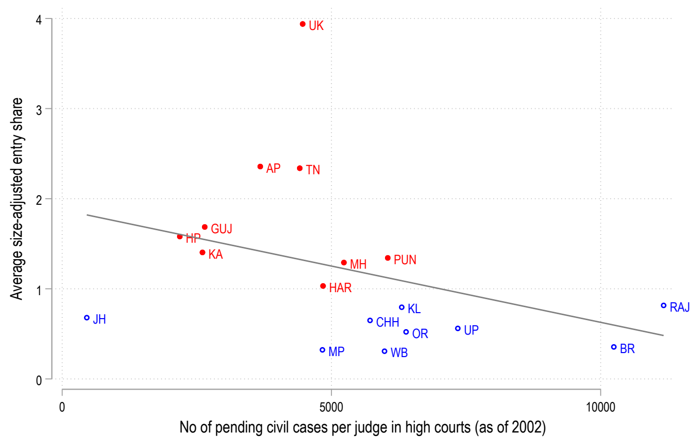

Figure B.3: Entry Shares vs No. of Pending Civil Cases per Judge in State High Courts

Notes: The figure above shows the relationship between size-adjusted entry shares, averaged from 1999 to 2018, and the number of pending civil cases per judge in the respective state high courts. In the figure, states with size-adjusted entry shares below 1 (low-performance states, in blue) have, on average, more pending civil cases per judge compared to states with size-adjusted entry shares of at least 1. The only exception to this is Jharkhand. Data on the number of pending civil cases per judge in state high courts has been taken from an official report published by the Ministry of Law and Justice, Government of India [Link].
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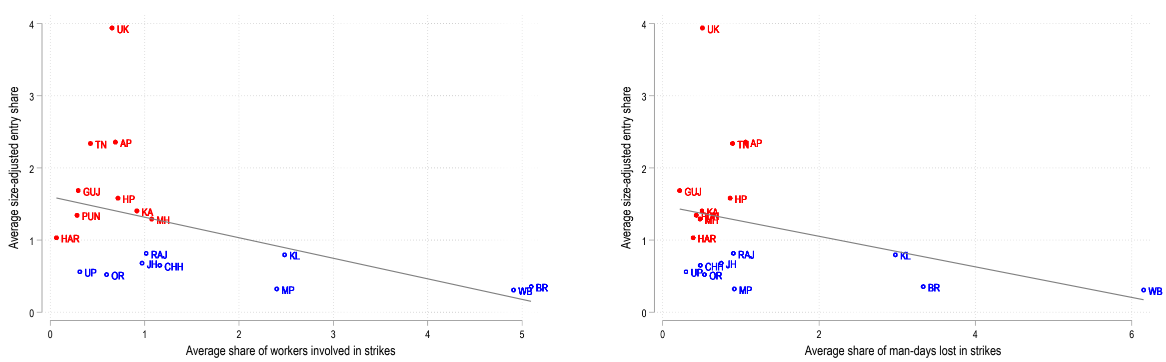
B.6 *Entry Shares versus Labor Unrest*

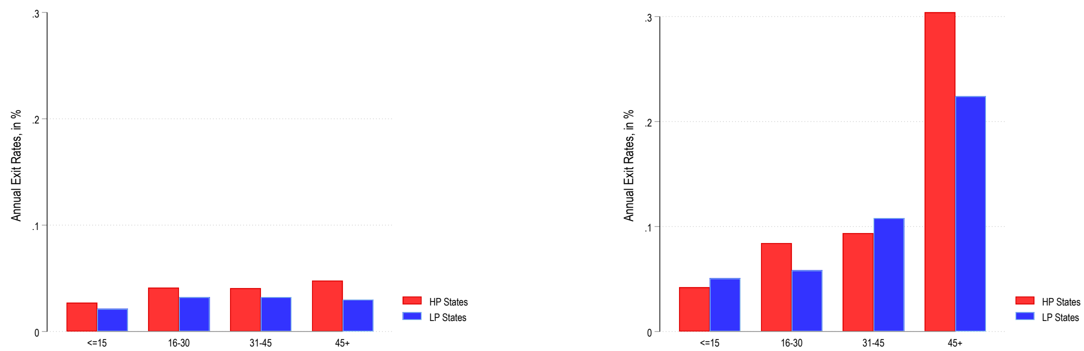


(a) Share of Workers involved in Strikes (b) Effects of changing labor adjustment cost

Figure B.4: Man-days lost in Strikes

Notes: The average share of workers involved in strikes and the share of man-days lost in strikes have been normalized by the overall share in the state. The left panel shows that states with size-adjusted entry shares below 1 (low-performance states, in blue) have, on average, a larger share of workers involved in strikes. Exceptions to this are Uttar Pradesh and Orissa. Data on the number of workers involved in strikes and man-days lost due to strikes is from the 'States of India' database provided by the Center for Monitoring of the Indian Economy.

B.7 Formal versus Informal Manufacturing Exit Rates



(a) Formal Manufacturing

(b) Informal Manufacturing

Figure B.5: Formal vs Informal Manufacturing Exit Rates: HP vs LP States

Notes: The left panel shows formal manufacturing plant exit rates across age cohorts for both state groups (this is identical to figure 3a in the paper, with the y-axis re-scaled to facilitate comparison with the right panel). The right panel shows informal manufacturing exit rates computed from NSS data for 1994-95 and 2015-16. The annual exit rate of informal manufacturing plants in high and low-performance states is 7% and 7.2%, respectively. There are two takeaways from the left and right panels: (1) Formal manufacturing plants have lower exit rates for all age cohorts than their informal manufacturing counterparts. (2) While high-performance states have consistently higher exit rates than low-performance states in formal manufacturing, there is no such pattern in informal manufacturing.

B.8 Labor Adjustment to Negative GVA Shocks

B.8.1 Heterogeneous Impact By Plant Size

Labor laws make firing particularly hard for plants employing more than a hundred workers. Therefore, we examine whether labor adjustment frictions in low-performance states are coming from larger plants. To do so, we estimate the below triple difference specification (this is a triple difference version of the regression specification in (1)).

$$\begin{aligned} Y_{ijst} &= \alpha_i + \alpha_{jt} + \alpha_{st} + \gamma' \mathbf{X_{ijst}} + \beta_1 \mathbb{1}\{Negshock_{it-1}\} + \beta_2 \mathbb{1}\{Negshock_{it-1}\} \times \mathbb{1}\{LP_s\} \\ &+ \beta_3 \mathbb{1}\{Above100_{it-1}\} + \beta_4 \mathbb{1}\{Negshock_{it-1}\} \times \mathbb{1}\{Above100_{it-1}\} \\ &+ \beta_5 \mathbb{1}\{LP_s\} \times \mathbb{1}\{Above100_{it-1}\} + \beta_6 \mathbb{1}\{Negshock_{it-1}\} \times \mathbb{1}\{LP_s\} \times \mathbb{1}\{Above100_{it-1}\} + \epsilon_{ijst} \end{aligned}$$

Here, $\mathbb{1}\{Above100_{it-1}\}$ equals 1 for plants employing more than 100 regular workers in year $t-1$, and is 0 otherwise. The estimated coefficients $\hat{\beta}_2$ and $\hat{\beta}_6$ are informative about whether small or large plants drive the differential response to negative shocks in low-performance states. Column 1 of table B.2 shows that negative shocks reduce employment of regular workers significantly, and that this is less so in LP states. In other words, it is the large plants – those with more than 100 regular workers – that drive the sluggish response of regular employment to negative shocks in low-performance states. Column 2 repeats column 1 with size-year fixed-effects (to account for differential trends by firm size), and the results remain robust. Columns 3 and 4 of table B.2 indicate no statistically significant difference in how large and small plants adjust their contract and managerial employment following negative shocks to value-added. Our results are qualitatively similar if we estimate specifications (3) and (4) below without size-year fixed-effects.

Table B.2: Heterogeneous impact of negative shocks on employment across state groups

Dependent Variable:	Log Employment			
	(1) Regular Workers	(2) Regular Workers	(3) Contract Workers	(4) Managers
$\mathbb{1}\{Neg\_shock_{it-1}\}$	-0.093***	-0.089***	-0.122***	-0.081***
	(0.005)	(0.005)	(0.012)	(0.005)
$\mathbb{1}\{Neg\_shock_{it-1}\} \times \mathbb{1}\{LP_s\}$	0.008	0.008	-0.002	0.011
	(0.008)	(0.008)	(0.022)	(0.007)
$\mathbb{1}\{Above100_{it-1}\}$	0.53***			
	(0.012)			
$\mathbb{1}\{Neg\_shock_{it-1}\} \times \mathbb{1}\{Above100_{it-1}\}$	0.001	-0.005	0.004	-0.005
	(0.008)	(0.008)	(0.021)	(0.008)
$\mathbb{1}\{LP_s\} \times \mathbb{1}\{Above100_{it-1}\}$	0.032	0.031	-0.034	0.031
	(0.022)	(0.022)	(0.046)	(0.017)
$\mathbb{1}\{Neg\_shock_{it-1}\} \times \mathbb{1}\{LP_s\} \times \mathbb{1}\{Above100_{it-1}\}$	0.027*	0.026	-0.004	-0.013
	(0.014)	(0.014)	(0.04)	(0.013)
N	223169	223169	106809	202645
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.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

B.8.2 Robustness to Finer Bins of GVA Shocks

Table 2 shows that plants in low-performing (LP) states fire fewer regular workers than their counterparts in high-performing (HP) states following negative GVA shocks. This could be because plants in LP states face larger firing costs, or negative shocks in LP states were not as severe as those in HP states. To rule out the second possibility, we do the following.

First, as before, we compute residuals (r_{ijst}) after regressing the inverse sine transformation of GVA on plant, industry-year, and state-year fixed effects. We then divide r_{ijst} into the following bins.

- $Bin_{ijst} = 1$ if r_{ijst} is below the 33rd percentile.
- $Bin_{ijst} = 2$ if r_{ijst} falls between the 33rd percentile and 66th percentile. Note $r_{ijst} = 0$ falls in this bin.
- $Bin_{ijst} = 3$ if r_{ijst} is at or above the 66th percentile.

Therefore, after a moderate shock to plant i's GVA in year t, Bin_{ijst} takes value 2. Following a very positive (or negative) shock to plant i's GVA in year t, Bin_{ijst} takes value 3 (or 1).

We then estimate the below specification with $Bin_{ijst-1} = 2$ as the base category. As before, the outcomes of interest are logarithms of regular, contract, and managerial employment. $\mathbb{1}\{LP_s\}$ takes 1 if the plant is located in a low-performing state, and 0 otherwise. α_i, α_{jt}, α_{st} are plant, industry-year, and state-year fixed-effects, respectively. X_{ijst} includes size-year fixed effects, to account for differential trends by plant size, and plant age. Results from estimating the equation below are in table B.3.

$$Y_{ijst} = \alpha_i + \alpha_{jt} + \alpha_{st} + \gamma'\mathbf{X_{ijst}} + \beta_1 Bin_{i_{jst-1}} + \beta_2 Bin_{i_{jst-1}} \times \mathbb{1}\{LP_s\} + \epsilon_{ijst}$$

Table B.3: Labor adjustment to GVA Shocks with finer bins

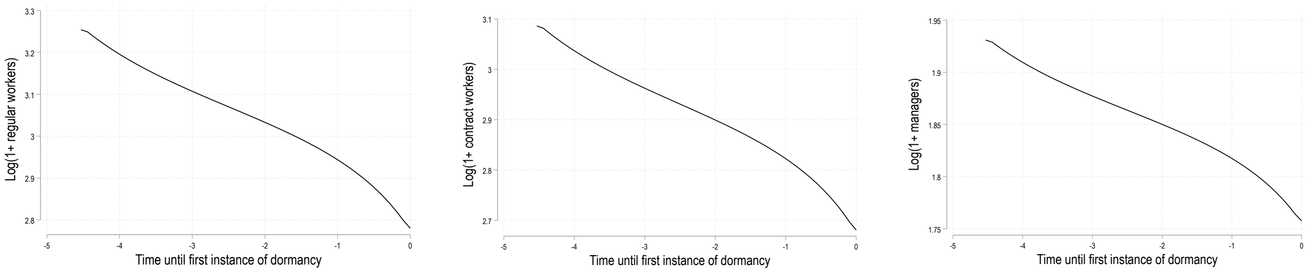
Dependent Variable:	Log Employment		
	(1)	(2)	(3)
	Regular Workers	Contract Workers	Managers
$Bin_{i_{jst-1}} = 1$	-0.074***	-0.102***	-0.067***
	(0.004)	(0.013)	(0.004)
$Bin_{i_{jst-1}} = 3$	0.057***	0.073***	0.046***
	(0.005)	(0.013)	(0.005)
$Bin_{i_{jst-1}} = 1 \times 1\{LP_s\}$	0.016*	0.025	0.011
	(0.007)	(0.023)	(0.007)
$Bin_{i_{jst-1}} = 3 \times 1\{LP_s\}$	-0.013	0.022	-0.000
	(0.008)	(0.025)	(0.008)
N	223169	106809	202645

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

The results indicate that, relative to the base category, plants with more negative GVA shocks experience a 7.4% decline in regular employment the following year. In contrast, those with more positive GVA shocks see a 5.7% increase in regular employment the subsequent year. These patterns hold for contract workers and managers as well. However, in LP states, the relationship between GVA shocks and regular employment is less monotonic. Regular employment in these states is less sensitive to GVA shocks, especially negative ones, compared to HP states. This is not the case for contractual and managerial employment. This suggests the presence of larger firing costs for regular workers in LP states, thereby confirming fact 4 in the main paper.

B.9 Inflation helps in shedding regular workers, and more so in low-performance states

As plants approach dormancy, they lay off workers – regular, contractual, and managers – as shown in figure B.6.



(a) Regular Workers (b) Contract Workers (c) Managers

Figure B.6: Plant Employment as they transition to dormancy

Notes: To plot these figures, we first residualize the y-variable and x-variable off plant fixed effects. Second, we rescale 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.

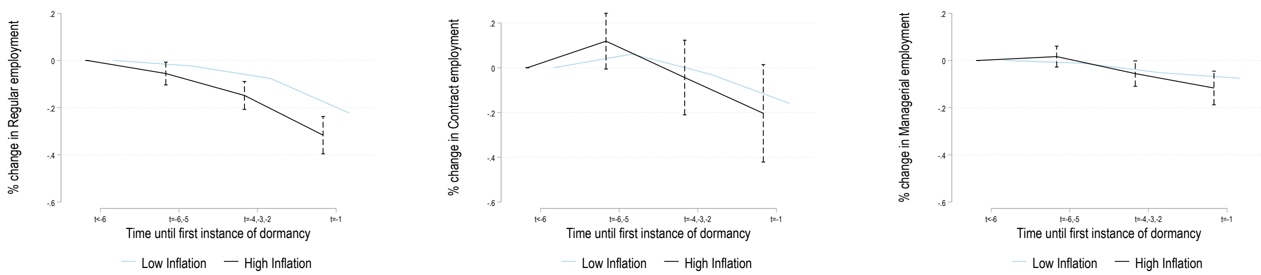
Although the adjustment of regular workers is hard because of labor regulations, plants still lay them off as they approach dormancy. How do they do it? We argue that one channel that they use to adjust labor is inflation. Plants on the path to dormancy, especially those in low-performance states and 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 low-performance states than in high-performance 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:

$$Y_{ijst} = \beta_0 + \sum_b \beta_1^b \left(D-t\right)_{ijst}^b + \beta_2^b \left(D-t\right)_{ijst}^b \times \mathrm{HI}_t + \mathbf{X}'_{ijst}\delta + \lambda_i + \lambda_{st} + \lambda_{jt} + \epsilon_{ijst}$$

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 the 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 the 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 B.7. The left panel corresponds to the logarithm of regular workers, the middle panel corresponds to the logarithm of contract workers, and the right panel corresponds to the 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.

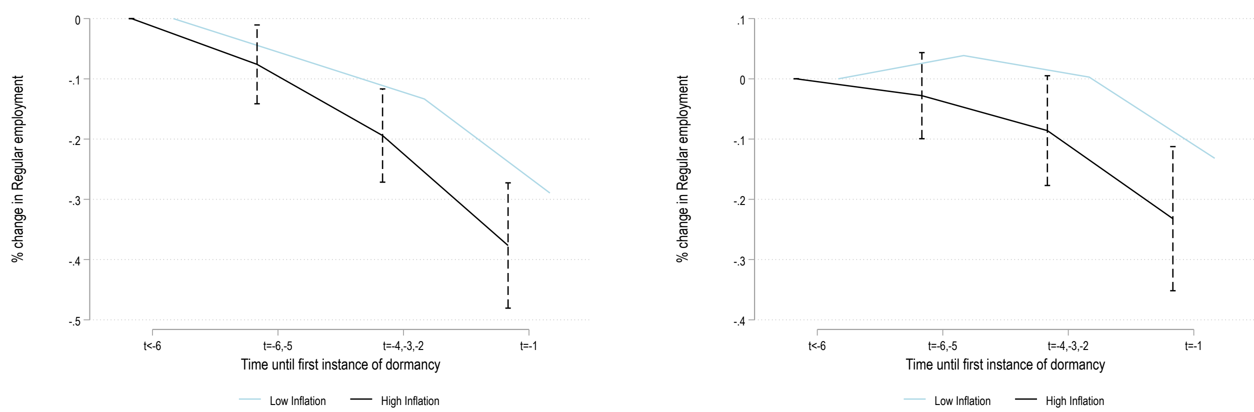
Figure B.7 shows that manufacturing plants in India on the path toward dormancy reduce employment–regular, contract, and managers. Compared to 6 years prior to dormancy, these plants have 22.2% fewer regular workers, 15.9% fewer contract workers, and 7.6% fewer managers in the year just prior to dormancy. There is a differential response in this labor adjustment process only for regular workers. Plants are likely to reduce 9.4% and 7.2% more regular workers in the year prior and 2-4 years prior to dormancy during high inflation years, as compared to normal



(a) Regular workers (b) Contract workers (c) Managerial workers

Figure B.7: Labor Adjustment and Inflation

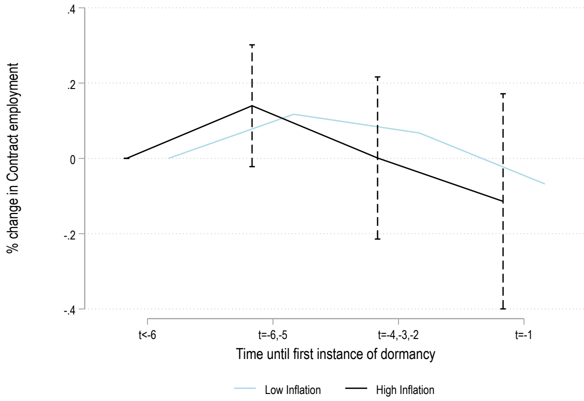
years. Next, in Figure B.8, we show that this differential adjustment of regular workers during high inflation periods primarily happens in low-performance states where, presumably, labor adjustment costs are much higher.[74] We find no differential effects for contract workers and managers between high-performance and low-performance states (see Figures B.9 and B.10).



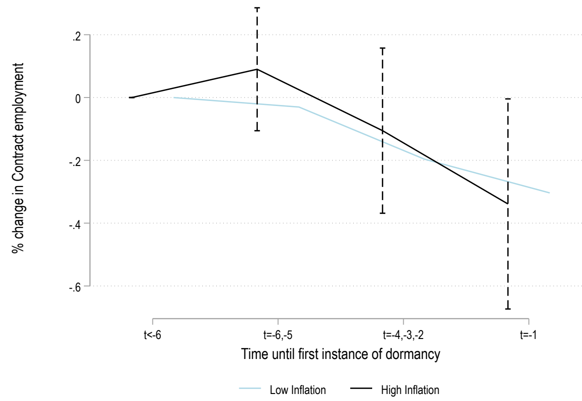
(a) High-Performance States (b) Low-Performance States

Figure B.8: Adjustment of Regular Workers and Inflation: HP vs LP States

[74]We introduce triple interactions in the regression model with an indicator for low-performance states.

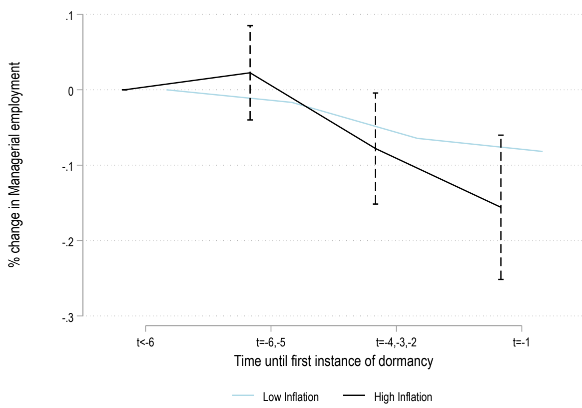


(a) High-Performance States

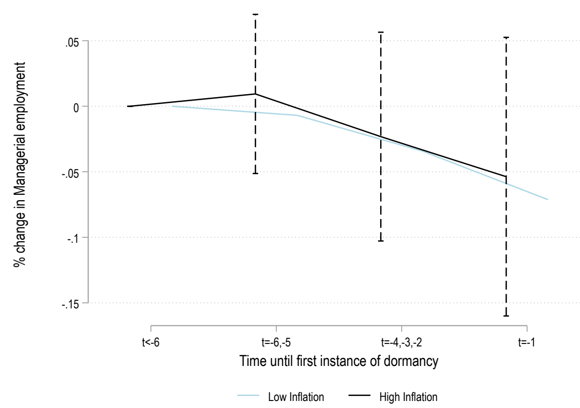


(b) Low-Performance States

Figure B.9: Adjustment of Contract Workers and Inflation: HP vs LP States



(a) High-Performance States



(b) Low-Performance States

Figure B.10: Adjustment of Managers and Inflation: HP vs LP States

C More Counterfactual Results

C.1 Expanded Table 5

Table C.4: Partial Equilibrium Counterfactuals – Target Exit Rate 4.5%

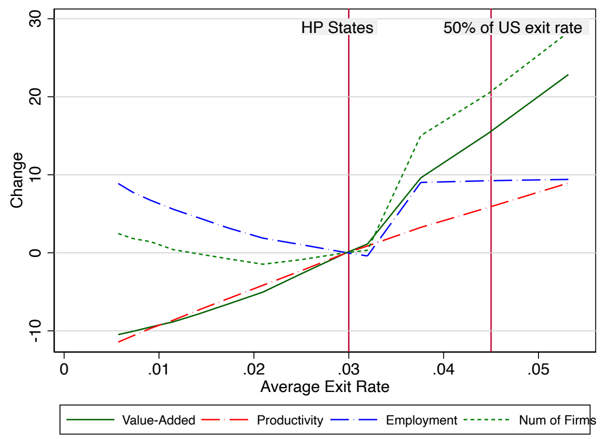
	Policy Instrument	Category	Baseline Exit Rate	Δ Value Added (%)	Δ Productivity (%) Aggregate	Entrants	Exiters	Δ Employment (%)	Δ Mass of Firms (%)	Dormancy Length (Δ years)	Age (Δ years)	Δ million rupees or Δ %
1	Exit Cost	LI / HP	2.98	9.61	3.25	-1.34	2.86	9.02	15.02	-0.50	-2.60	168.75
2		LI / LP	2.23	4.81	3.00	-1.22	3.66	-0.37	3.30	-0.57	-2.84	168.75
3		CI / HP	4.46	21.25	3.43	-2.08	8.72	10.23	25.40	-0.59	-3.00	168.75
4		CI / LP	3.32	17.91	2.94	-2.29	6.37	8.35	21.07	-4.23	-3.25	168.75
5		Aggregate India	3.45	14.27	3.23	-1.73	5.54	8.08	17.98	-1.09	-2.87	168.75
6	Labor Adj Cost	LI / HP	2.98	14.28	4.45	-1.03	2.94	-7.76	20.63	-0.55	-2.73	-62.88%
7		LI / LP	2.23	9.19	4.28	-1.07	3.46	-17.32	7.55	-0.70	-3.35	-62.88%
8		CI / HP	4.46	20.07	3.33	-1.34	8.00	-17.80	22.90	-0.52	-2.62	-62.88%
9		CI / LP	3.32	19.41	3.21	-1.74	7.89	-21.27	21.57	-4.15	-3.29	-62.88%
10		Aggregate India	3.45	16.38	3.85	-1.25	5.51	-14.56	19.81	-1.09	-2.86	-62.88%

Note: This table presents counterfactual estimates of various aggregate outcomes like value added, productivity, employment, etc. that result from changing one of two policy instruments: exit costs (rows 1-5) or labor adjustment costs (rows 6-10). The data is divided into four state-industry groups as mentioned in rows 1-4 and 6-9. We calculate the relevant policy change such that the average exit rate for the aggregate India becomes 4.5%. For each group separately, we estimate the counterfactual with the same size of the policy change. These results are reported in rows 1-4 and 6-9. Here, LP: Low-performance States, HP: High-performance states, LI: Labor-Intensive Industries, CI: Capital-Intensive Industries.

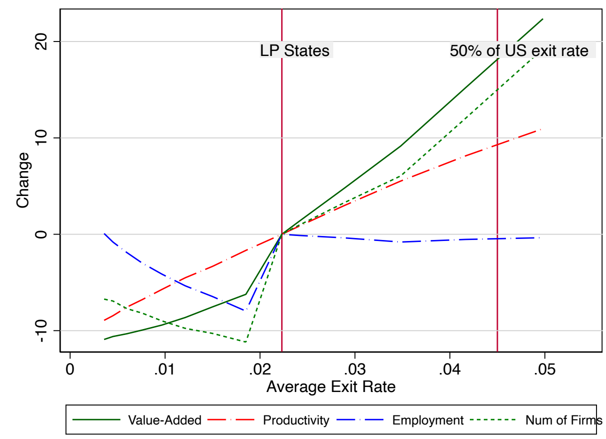
Note that as the same exit costs/proportional labor adjustment cost changes are applied to all state groups, the outcomes in each state group are very different from the weighted average case. For example, the LI/LP group has the smallest increase in value added of all four groups, both when scrap value is raised and when labor adjustment costs are reduced. Moreover, even when the scrap value is reduced, employment falls (slightly) in the LI/LP group, though it rises in all the other groups. Entrants become less productive and exiters more productive, in each of the four groups, due to reductions in exit costs or labor adjustment costs.

C.2 Counterfactual Results of Four Cases Separately

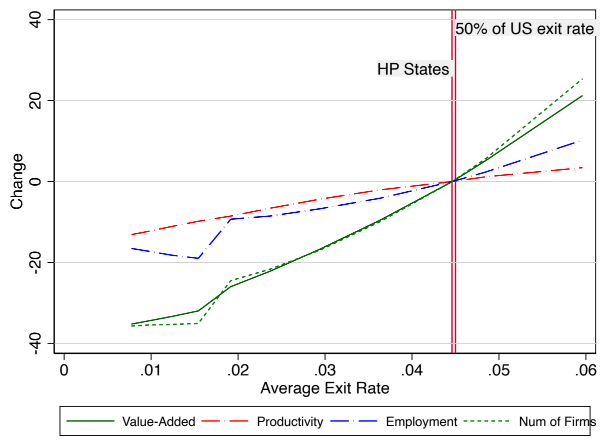
Figure C.11 and Figure C.12 present the counterfactual of policies changing exit and labor adjustment costs in four cases (Labor-intensive in High-performance states, Labor-intensive in Low-performance states, Capital-intensive in high-performance states and Capital-intensive in Low-performance states) separately. This corresponds to Figure 6 in the paper but for each of the four cases seperately.



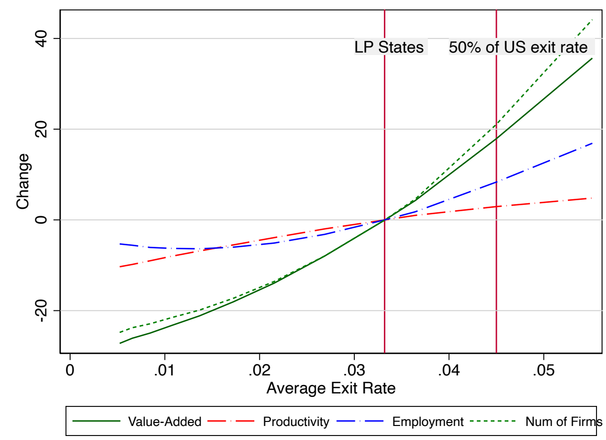
(a) LI sector in HP states



(b) LI sector in LP states



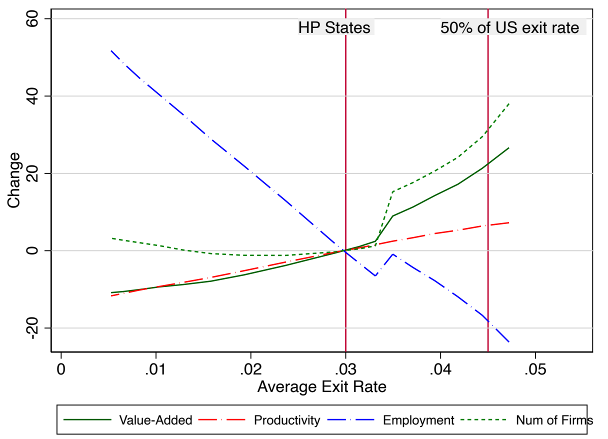
(c) CI sector in HP states



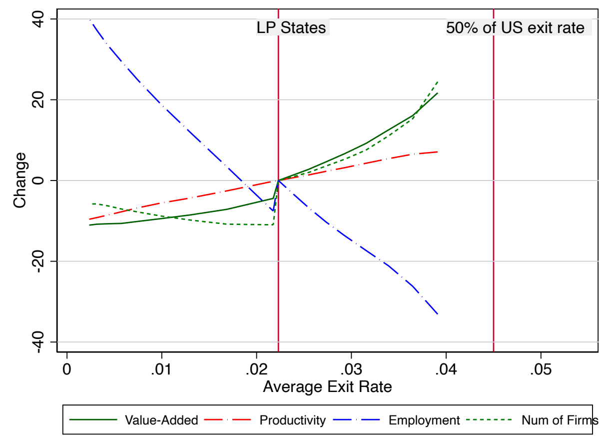
(d) CI sector in LP states

Figure C.11: Counterfactual of Changing Exit Costs in Four Cases Separately

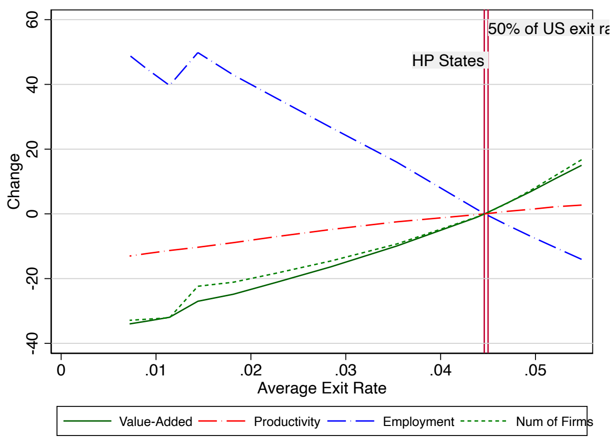
Notes: LP: Low-performance States, HP: High-performance states, LI: Labor-Intensive Industries, CI: Capital-Intensive Industries.



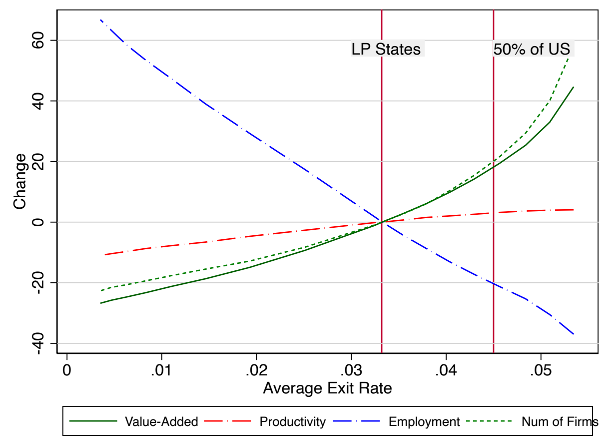
(a) LI sector in HP states



(b) LI sector in LP states



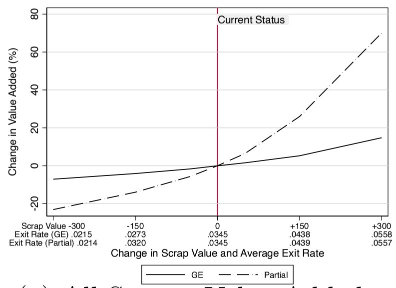
(c) CI sector in HP states



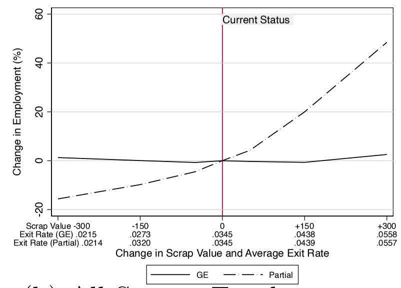
(d) CI sector in LP states

Figure C.12: Counterfactual of Changing Labor Adjustment Costs in Four Cases Separately

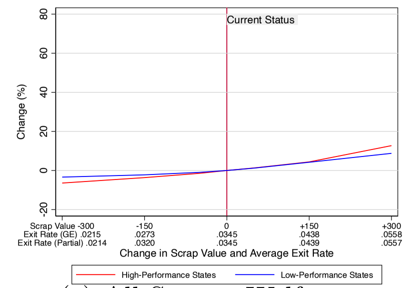
Notes: LP: Low-performance States, HP: High-performance states, LI: Labor-Intensive Industries, CI: Capital-Intensive Industries.



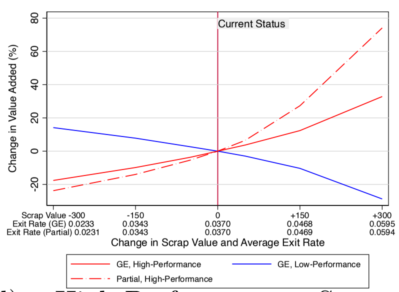
(a) All States: Value Added



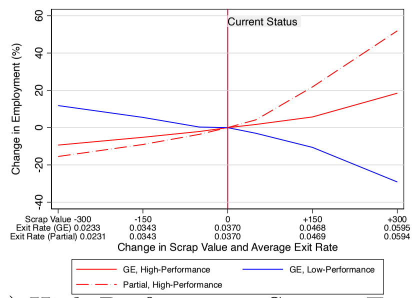
(b) All States: Employment



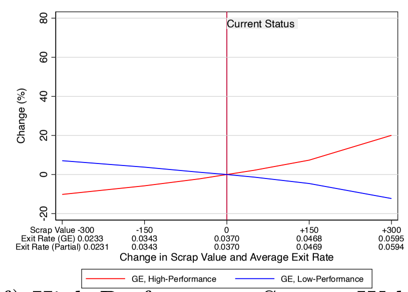
(c) All States: Welfare



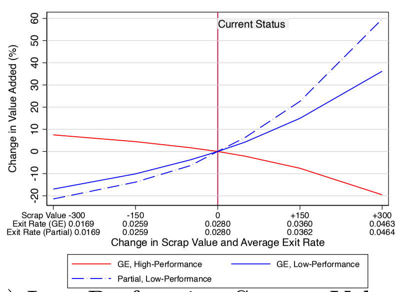
(d) High-Performance States: Value Added



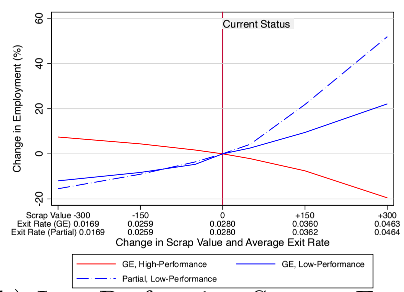
(e) High-Performance States: Employment



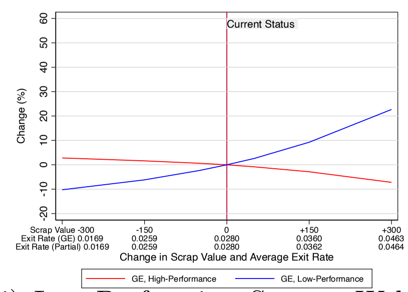
(f) High-Performance States: Welfare



(g) Low-Performing States: Value Added

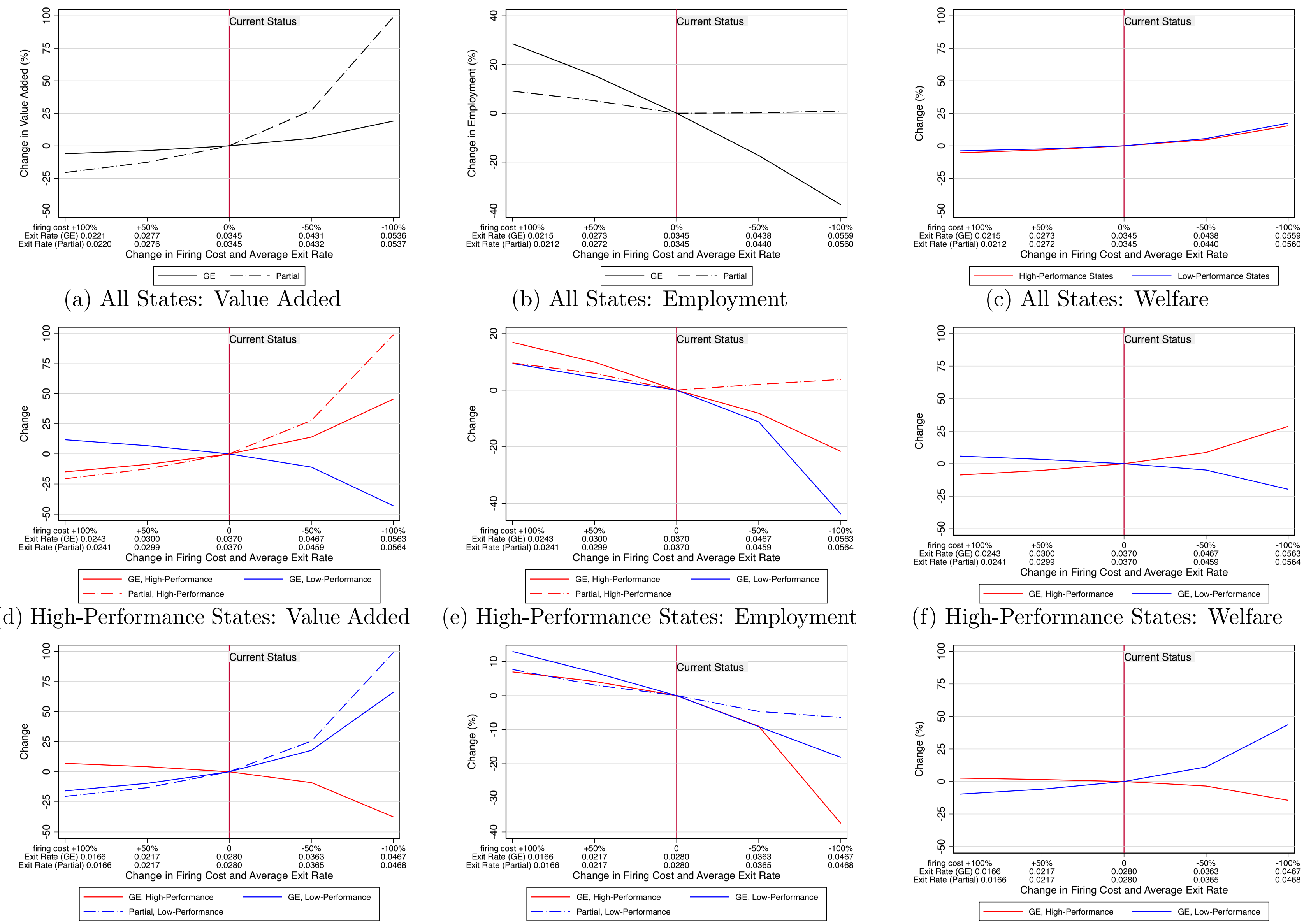


(h) Low-Performing States: Employment



(i) Low-Performing States: Welfare

Figure C.13: General Equilibrium vs Partial Equilibrium: Increasing Scrap Value



(a) All States: Value Added
(b) All States: Employment
(c) All States: Welfare
(d) High-Performance States: Value Added
(e) High-Performance States: Employment
(f) High-Performance States: Welfare
(g) Low-Performance States: Value Added
(h) Low-Performance States: Employment
(i) Low-Performance States: Welfare

Figure C.14: General Equilibrium vs Partial Equilibrium: Reducing firing cost

D Estimation Procedure

D.1 Quasi-Likelihood function

As described above in section 6.1, we begin by estimating the auxiliary parameters corresponding to the structural parameters. Even though we have to estimate the auxiliary models only once, this is still computationally intensive as each iteration of the optimization algorithm requires resolving the Bellman equation and the policy functions. Following Golombek and Raknerud (2018), we partition the set of θ parameters that we estimate into three sets. The parameters that govern (a) the firm's static choices, including prices and intermediate inputs, (b) the decision to produce or be dormant within each period, and (c) the dynamic decisions of the firm, e.g., labor and capital, and the decision to exit or stay. It is the third set of parameters that is computationally most intensive to estimate, and reducing that set is efficient. We estimate the quasi-likelihood function for each set of the parameters as elaborated as follows.

Parameter Group 1: $\theta_1 = \{\tilde{\gamma}_0, \tilde{\gamma}_1, \sigma_\gamma^\varepsilon\}$

We first compute the profitability of firms $\tilde{\phi}_{it}$ by calculating the Solow residuals based on equations (5). Note from equations (5) and (6) that if we treat current and past choices of firms about labor and capital (i.e. $L_{i,c}, L_{i,r}, K_i$) as exogenous, then the likelihood of observing a certain value added in the data depends only on θ_1 and calibrated parameters. This likelihood function assumes that labor and capital are exogenous and violate the structural model, and hence is a quasi-likelihood function rather than a component of the likelihood function. It allows us to estimate θ_1^a using the following simple log-likelihood function of θ_1^a.

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

$$\ln l_1(\theta_1^a; \tilde{\phi}_i) = \sum_{t=1}^{T} \mathbb{1}\{z_{it} = P; z_{it-1} = P\} \ln f_{\theta_1^a}(\ln \tilde{\phi}_{it} | \ln \tilde{\phi}_{it-1}) \tag{D.18}$$

where, $f_{\theta_1^a}(\ln \tilde{\phi}_{it} | \ln \tilde{\phi}_{it-1})$ is the density of normal distribution implied by Eq (6). Thus, $\hat{\theta}_1^a$ maximizes the following objective function given data Y_{Data}.

$$\ln L_1(\theta_1^a; Y_{Data}) = \sum_i \ln l_1(\theta_1^a; \tilde{\phi}_i) \tag{D.19}$$

Parameter Group 2: $\theta_2 = \{\mu_f^{PP}, \mu_f^{DP}, \sigma_P\}$

These parameters only govern the firm's choice to produce or be dormant. This choice is made after labor, capital, and fixed cost shocks have occurred, and subsequent factor payments do not depend on it. From equation (5) and given $\hat{\theta}_1^a$ from step 1, we can construct an approximation of $\tilde{\phi}_{it}$ as $\hat{\tilde{\phi}}_{it} = \frac{VA_{it}}{L_{i,t}^{\alpha_L} K_{i,t}^{\alpha_K}}$. The quasi log-likelihood function of θ_2 is constructed based on whether firms find it profitable to produce or not after paying the fixed production cost. Strictly speaking, the choice of production or dormancy also affects firms' future value function through the hysteresis of production cost. To reduce the computation burden, we ignore the hysteresis of the production cost when we construct the quasi-likelihood function for θ_2. Therefore, the quasi log-likelihood function of θ_2, which basically reflects probabilities to produce and be dormant, allows us to estimate θ_2^a.

$$\begin{aligned}\log l_2(\theta_2^a; \tilde{\phi}_{it}, L_{i,ct}, L_{i,rt}, K_{it}, \hat{\theta}_1^a) = \log \Pr\{&VA(\tilde{\phi}_{it}, L_{i,ct}, L_{i,rt}, K_{it}) \\ &- \mathbb{1}\{S_{it-1} = P\} f^{PP} - \mathbb{1}\{S_{it-1} = D\} f^{DP} > 0\}\end{aligned} \tag{D.20}$$

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

$$\ln L_2(\theta_2^a; Y_{Data}, \hat{\theta}_1^a) = \sum_{i,t} \ln l_2(\theta_2^a; \tilde{\phi}_{it}, L_{i,ct}, L_{i,rt}, K_{it}, \hat{\theta}_1^a) \tag{D.21}$$

Parameter Group 3: $\theta_3 = \{c_{Hc}, c_{Fc}, c_{Hr}, c_{Fr}^L, c_{Fr}^S, c_{HK}, c_{FK}, \sigma_{Lc}^\varepsilon, \sigma_{Lr}^\varepsilon, \sigma_K^\varepsilon, c_{FK}^E, \mu_f^E, \sigma_E\}$

These remaining 13 parameters pertain to various adjustment costs, shocks to inputs, and scrap values. They govern the firms' dynamic choices and can be estimated using a likelihood function for observing values of labor and capital and exit choices that we see in the data. This step is computationally the most demanding part of our estimation procedure, as it requires re-estimating the value function for each trial value of θ_3^a

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

$$\ln l_3(\theta_3^a; \hat{\theta}_1^a, \hat{\theta}_2^a, Y_{Data}) = \sum_{t=1}^{T} \mathbb{1}\{z_{it-1} = P\} \ln g_{(\theta_3^a; \hat{\theta}_1^a, \hat{\theta}_2^a)}(L_{i,ct}, L_{i,rt}, K_{i,t}, z_{i,t} | \hat{\tilde{\phi}}_{it}, L_{i,ct-1}, L_{i,rt-1}, K_{i,t-1}) \tag{D.22}$$

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

$$\begin{aligned}&g_{(\theta_3^a; \hat{\theta}_1^a, \hat{\theta}_2^a)}(L_{i,ct}, L_{i,rt}, K_{i,t}, z_{i,t} | \hat{\tilde{\phi}}_{it}, L_{i,ct-1}, L_{i,rt-1}, K_{i,t-1}) = \\ &\quad g_{(\theta_3^a, \hat{\theta}_1^a, \hat{\theta}_2^a)}(L_{i,ct}, L_{i,rt}, K_{i,t} | z_{i,t}, \hat{\phi}_{i,t}, L_{i,ct-1}, L_{i,rt-1}, K_{i,t-1}) \times p_{(\theta_3^a, \hat{\theta}_1^a, \hat{\theta}_2^a)}(z_{i,t} | \hat{\phi}_{i,t}, L_{i,ct-1}, L_{i,rt-1}, K_{i,t-1}).\end{aligned}$$

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.

$$\begin{aligned}&p_{(\theta_3^a, \hat{\theta}_1^a, \hat{\theta}_2^a)}(z_{i,t} = P | s_{i,t}) = Prob\{z_{it} = P | s_{it}\} \times (1 - p_{missing}(L_{i,ct-1}, L_{i,rt-1}, K_{i,t-1})) \\ &p_{(\theta_3^a, \hat{\theta}_1^a, \hat{\theta}_2^a)}(z_{i,t} = D | s_{i,t}) = Prob\{z_{i,t} = D | s_{it}\} \times (1 - p_{missing}(L_{i,ct-1}, L_{i,rt-1}, K_{i,t-1})) \\ &p_{(\theta_3^a, \hat{\theta}_1^a, \hat{\theta}_2^a)}(z_{it} = E | s_{i,t}) = \\ &\qquad \sum_{t'=t}^{\overline{T}} \left\{ \Pi_{\tau=t}^{t'} Prob\{z_{i,\tau} = P \text{ or } D | s_{it}\} \times p_{missing}(L_{i,ct-1}, L_{i,rt-1}, K_{i,t-1}) \times Prob\{z_{i,t'} = E | s_{it}\} \right\} \\ &p_{(\theta_3^a, \hat{\theta}_1^a, \hat{\theta}_2^a)}(z_{it} = M | s_{i,t}) = 1 - p_{(\theta_3^a, \hat{\theta}_1^a, \hat{\theta}_2^a)}(z_{i,t} = P | s_{i,t}) - p_{(\theta_3^a, \hat{\theta}_1^a, \hat{\theta}_2^a)}(z_{i,t} = D | s_{i,t}) - p_{(\theta_3^a, \hat{\theta}_1^a, \hat{\theta}_2^a)}(z_{it} = E | s_{i,t})\end{aligned} \tag{D.23}$$

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,

$$g_{(\theta_3^a,\hat{\theta}_1^a,\hat{\theta}_2^a)}(L_{c,it}, L_{r,it}, K_{i,t}|z_{i,t}, s_{i,t}) = f_c(L_{c,it}|h_c(s_{i,t}), \sigma^{\varepsilon}_{Lc}) \cdot f_r(L_{r,it}|h_r(s_{i,t}), \sigma^{\varepsilon}_{Lr}) \cdot f_K(K_{i,t}|h_K(s_{i,t}), \sigma^{\varepsilon}_{K})$$

where, $f_c(\cdot)$ is the pdf of a log normal distribution with mean $h_c(\cdot)$ and standard deviation σ^{ε}_c as defined in Eq (11). $f_r(\cdot)$ 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.

$$\begin{aligned}
&g_{(\theta_3^a,\hat{\theta}_1^a,\hat{\theta}_2^a)}(L_{i,ct}, L_{i,rt}, K_{i,t}, z_{i,t}|\hat{\hat{\phi}}_{it}, s_{i,t}) \\
&\quad = \begin{cases} g_{(\theta_3^a,\hat{\theta}_1^a,\hat{\theta}_2^a)}(L_{c,it}, L_{r,it}, K_{i,t}|z_{i,t} = P, s_{i,t}) \cdot p_{(\theta_3^a,\hat{\theta}_1^a,\hat{\theta}_2^a)}(z_{i,t} = P|s_{i,t}) \\ p_{(\theta_3^a,\hat{\theta}_1^a,\hat{\theta}_2^a)}(z_{i,t}|s_{i,t}) \qquad \text{if } z_{i,t} = D, M, E \end{cases}
\end{aligned}$$

Adding the likelihood components of each firm as defined in Eq (D.22) gives the likelihood function as follows

$$\ln L_3(\theta_3^a; \hat{\theta}_1^a, \hat{\theta}_3^a), Y_{Data}) = \sum_i \ln l_3(\theta_3^a; \hat{\theta}_1^a, \hat{\theta}_2^a, Y_{Data}) \tag{D.24}$$

We obtain the partial quasi-likelihood estimator of θ_3^a by maximizing Eq (D.24) 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.

D.2 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

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

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.

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

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 $z^{(s)}_{it}(\theta)$ with its conditional expectation given the simulated state variables $\hat{z}^{(s)}_{it}(\theta)$. That is, $\hat{z}^{(s)}_{it}(\Theta)$ is a conditional probability of each possible state P, D, M and E.

Next, we explain how to calculate the smoothed trajectories $Y^{*(s)}_{Sim}$.
Let θ be given (We use $\hat{\theta}^a$ as the initial value).

1. Solve Equation (14) and the corresponding optimal capital ($\overline{K}^s_{it}$) and labor adjustment ($\overline{L}^s_{i,ct}$ and $\overline{L}^s_{i,rt}$).
2. For given i and s: Set $t = 1$ and $K^{(s)}_{i0} = K_{i0}$, $L^{(s)}_{i,c0} = L_{i,c0}$ and $L^{(s)}_{i,r0} = L_{i,r0}$ (the actual initial value of firm i).
3. Draw $\tilde{\phi}^{(s)}(\theta)$ from Equation (3).
4. Draw $L^{(s)}_{i,ct}$, $L^{(s)}_{i,rt}$ and $K^{(s)}_{i,t}$ as explained in Sections 5.3.1 and 5.3.2.
5. For $t = 1$: set $Prob(\hat{z}^{(s)}_{it}(\theta) = P) = 1$. For $t > 1$: calculate the probability of states $Prob\{z_{it} = P|s_{it}\}$, $Prob\{z_{it} = D|s_{it}\}$ and $p_{missing}(L_{i,ct-1}, L_{i,rt-1}, K_{i,t-1})$. Calculated backward from $T + 1$, we derive the probability of each state $p_{(\theta)}(\hat{z}^{(s)}_{it}(\theta)|s_{i,t})$. Set $Prob(\hat{z}^{(s)}_{it}(\theta)) = \Big(p_{(\theta)}(\hat{z}^{(s)}_{it}(\theta)|s_{i,t})\Big) \times \Big(Prob(\hat{z}^{(s)}_{it}(\theta) = P, D\Big)$.
6. For $t = T + 1$: stop.
7. Set $t = t + 1$ and go to 3.