NO COUNTRY FOR DYING FIRMS: EVIDENCE FROM INDIA

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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.

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1. INTRODUCTION

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.

We study India's manufacturing sector for three reasons. First, there are several puzzles related to India's development that 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 explains all three of these as a consequence of exit barriers. As we argue below, manufacturing has more exit barriers for institutional reasons.[1] Since exit barriers act like entry barriers, manufacturing, especially labor-intensive manufacturing, becomes less attractive. Exit barriers also induce firms that want to exit to remain.

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 reason to expect evidence that exit costs in India are high. Manufac-

[1] The Industrial Disputes Act (IDA), which applies to manufacturing, plantations, and mines, makes firing workers (which would be needed to exit) very difficult, especially for large firms.

turing in India has one of the lowest firm exit rates in the world (see Figure 1a below).[2] Exit rates in sectors that are not specifically covered by the IDA are roughly twice as high (see Figure 1b).[3] Many firms in India remain dormant[4] (produce nothing, with or without workers) for a long time before they finally exit, and are often supported by lending from state owned banks.[5] 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 compared to about 12 months in Singapore, 12-24 months in Germany, and 15 months in the United Kingdom (Economic Survey of India 2020-21).

Although our empirical context in this paper is India, these economic mechanisms are of broad relevance. For example, it has been argued that part of the reason why the US performed better post-COVID lay in its different pandemic responses. While Europe's strategy focused on preserving jobs and firms (which inadvertently caused economic rigidity), the US unconditionally subsidized firms that claimed to be hurt and provided direct payments to laid-off workers. This gave workers a safety net that allowed them to search for a better job match and greater resilience and dynamism post-COVID.[6]

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. These data patterns are novel and a contribution in themselves.

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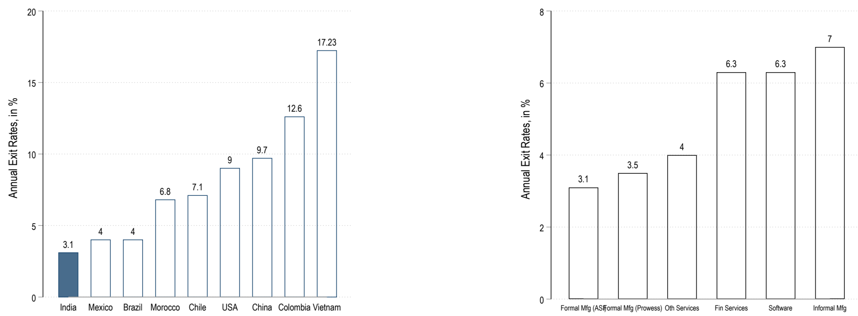
[2] While no direct exit measure is available in the ASI data, we follow Hsieh and Klenow (2014) to measure exit rates. They proposed comparing the mass of plants from a specific vintage (i.e., the initial year of production) from ASI survey rounds, e.g., in years t and $t + \Delta$. Since the sample 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.

[3] Exit rates are also much lower in formal manufacturing than in informal manufacturing, as shown in Figure B.3 in the Online Appendix.

[4] 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.

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

[6] 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.



(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.

Second, we build and estimate a rich dynamic model of firm behavior, capable of capturing the relevant features in the Indian setting, in the presence of exit costs. 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. Our estimated parameters suggest that both labor adjustment costs and bankruptcy cost as captured in scrap value are high, and more so in low-performing states.

We use the estimated model to conduct policy counterfactuals. 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. In partial equilibrium, where the price index and income level are fixed, we find that both policies increase aggregate value added, but the first reduces employment while the second raises it. For example, if we set the policies to result in an exit rate of

4.5% that is half of the US one, the value added increases by 16% with the first policy and 14% with the second. Employment falls by 15% with the first policy, but increases by 8% with the second. We also find that there are strong synergies between the two policy instruments. The effect of implementing both policies together on value added is greater than the sum of the parts. Our result suggests that if labor regulations are relaxed after bankruptcy reform, the adverse employment effects could be avoided. In addition, we find that with a fixed budget, entry subsidies raise value added less than exit subsidies, but the reverse is true for employment. In general equilibrium, where both the price index and income are endogenized, the effects tend to be more muted.

Our work is related to a number of strands in the literature. It is, of course, related to the literature on entry and exit costs. 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. Alfaro and Chari (2009) finds that the deregulation of entry barriers in India led to a thickening of the left tail of the firm size distribution but mattered little for firm growth. Our focus is on exit costs overall. The existing literature on exit costs has focused on a country's specific regulations or frictions, rather than on exit costs as a whole. For example, Besley and Burgess (2004), Chaurey (2015), Garicano et al. (2016), Bertrand et al. (2021), and Chaurey et al. (2023) study labor regulations, Di Martino (2005), Bignon and Sgard (2007), Alok et al. (2022), and Li and Ponticelli (2022) study bankruptcy regulations, while Sood (2020) looks at frictions in the market for land. Rather than constraining ourselves to a particular source of exit costs, we capture a plethora of measurable and unmeasurable exit costs using our approach. For example, our estimate of scrap value captures all the factors that create fixed costs that reduce the value of exit. These could be bribes to be paid, or time needed to get clearance from the authorities, or to smooth the way for selling land or buildings.

Our work also connects to the literature on labor market adjustment costs which are part of exit costs as workers must be fired for a firm to exit. Most of this literature has focused on the consequences of firing costs. Papers span both reduced form (e.g. Besley and Burgess, 2004) and structural methods (e.g. Cooper and Willis, 2009). Reduced form models typically classify the extent of such costs by creating indices based on variations in the law or delays in courts. An example of this is the Besley-Burgess index, see Besley and Burgess (2004), which has been used to classify states as pro-worker or pro-business.

However, it has been highly criticized on many fronts, see Bhattacharjea (2006). As the implementation of laws is imperfect, and much is left to the discretion of the courts and authorities, it is difficult to create an index based on the letter of the law.[7] The decisions of the lower courts are usually extreme and often overturned by the higher courts.[8] Also, there are many non-legal reasons, like political constraints, that create exit costs and are not fully captured by the indices. Building on Cooper and Willis (2009), our approach is able to estimate labor adjustment costs through the behavior of firms in response to changing economic conditions. This captures the law, its implementation, as well as other observable or unobservable labor market adjustment costs.

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.

In sum, our contribution to the literature is as follows. We are the first to make the case that exit barriers, broadly defined, play an important role in explaining Indian's pattern of development. We do so by showing data patterns consistent with this, and then by modeling exit barriers in a much more flexible and comprehensive manner than in the literature. Our model allows for enough flexibility to capture the heterogeneity that we see in the data,

[7] For example, it is not clear 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?

[8] 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.

and reduced form analysis in Section 4. Second, we are the first to be able to speak to the macroeconomic consequences of reform. We provide insight into the effect of reforms on key economic variables like entry and exit rates, productivity, and value added. Third, we provide new results on the efficacy of, and synergies between policies, as well as implications for the sequence in which to implement them in order to meet conflicting objectives like employment and income.

The paper proceeds as follows. In Section 2, we provide some details about the institutional context.[9] 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. A significant portion of this time, 2.8 years, is spent on obtaining clearances and security refunds from various government departments, including Income Tax, Provident Fund, Goods and Services Tax, among others. 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 various central and state laws regulate worker retrenchment and firm liquidation, 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

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

regulatory framework is not the only obstacle to firm exit. Political interference, a clogged judicial system, strikes, lockouts, and extra-judicial pressures—including the influence of local strongmen— can also prevent firm closures.

This section aims to highlight various factors that contribute to exit costs in India. Not all of them are observable or measurable. Thus, it would be impossible to quantify, even approximately, 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.

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 time, it sold approximately one 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 nearly 20,000 employees and produced 15 million phones per 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.[10] 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

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

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. General Motors and Ford also had a taste of trying to exit under Indian conditions.[11]

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. Amongst other things, it puts additional restrictions on firing workers in firms with more than 100 workers. However, this law has been reformed and implemented differentially between states, leading to cross-state variation in labor adjustment frictions (Besley and Burgess, 2004). 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). 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

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

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.

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.[12] . 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.[13] For example, in May 2025, the Indian Supreme court issued a shocking judgment that struck down the liquidation of a steel company that had been deemed complete four years ago, setting a troubling precedent and casting a shadow of uncertainty on all future liquidations and acquisitions.[14]

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

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

[14]see Indian Supreme Court's shock ruling against JSW Steel.

3. DATA & MEASURING EXIT

We use data from 1999 to 2018 of the Annual Survey of Industry (ASI), the official annual survey of India's formal manufacturing sector. The ASI is a panel that covers all establishments with more than 100 employees, and every year, a fifth of all establishments with more than 20 employees (or more than 10 if they use power). The ASI includes fixed assets, working capital, loans, employment, input items, products and by-products produced, other expenses, and receipts.

The key feature of the ASI that makes it uniquely valuable for us is that it records the status of establishments as either "active" or "dormant". "Dormancy" occurs when the firm has capital or labor, but does not engage in production. Details on inputs, factor payments, assets, and debt are recorded even when the establishment is dormant. Extended periods of dormancy with sluggish adjustment of factors of production are indicative of exit frictions.

Establishments could be dropped from the panel either because they had fewer than 10 workers, had been dormant without workers for more than three years, or had exited. Thus, while the ASI does not explicitly record the "exit" of establishments, there are two ways of estimating it. First, by exploiting the representativeness of the data, exit is calculated as the reduction in the mass of establishments of a specific vintage over time (à la Hsieh and Klenow (2014)). Second, we classify an establishment as having exited if it disappears from the sample and then does not re-appear until the end of the panel and for at least 10 years. Both methods yield similar magnitudes.

4. FACTS

This section presents a set of novel facts that suggest the presence of substantial exit costs, their variation across states, and how firms respond to these frictions.

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

There is significant variation in formal manufacturing activity across Indian states. On the y-axis of Figure 2, we plot each state's average entry share from 1999 to 2018. In a given year, a state's entry share is the proportion of total entrants that go to that state, normalized by its population share. Thus, if a state's average entry share is greater (lower) than 1, it attracts more (fewer) entrants relative to its size. Similarly, the x-axis of Figure 2 shows each state's exit share, normalized by its population share. Following Hsieh and Klenow (2014), we first compute cohort-specific exit shares for each state from 2001 to 2016. A state's exit share is, then, the weighted average of its cohort-specific exit shares, with the fraction of plants belonging to each cohort in 2001 in the state as weights. Appendix B.1 provides further details. Figure 2 shows that states with higher exit shares, represented in red, have higher entry shares, and vice-versa. This makes sense as potential entrants will not want to enter states with restrictive exit conditions, and in steady state, entry and exit shares should be the same.

To provide further evidence that states with low entry (and exit) suffer from various institutional frictions, we show in Appendix Figure B.1 that states with lower entry have higher misallocation. Entry shares are also negatively correlated with specific institutional barriers to exit. For instance, Appendix Figures B.2a and B.2b show that entry shares across states are inversely related to court congestion and labor unrest/strikes, respectively.

Ideally, we'd want to conduct our analysis at the state level, since that is the administrative level at which many policies related to exit are set. However, the data is too sparse for certain states, especially those with low entry. Hence, we pool data to 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). We acknowledge that our classification is based on endogenous variables; however, note that our goal in this section is to illustrate heterogeneity. Our structural model uses other well-identified moments to pin down exit costs and economic fundamentals.

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.*

Figure 3a shows that exit rates are systematically lower in LP states across cohorts of manufacturing establishments, especially among older plants. These low exit rates suggest higher exit barriers in LP states than in HP states. Consistent with this interpretation, we find that LP states also exhibit a long right tail of very old, low-productivity plants that are absent in HP states. In particular, the bottom Figure 3b shows a stark difference in the age distribution of plants (right axis): in 1999, the 99th percentile of plant age was 95 years in LP states, compared to 68 years in HP states—a gap that has persisted over time.

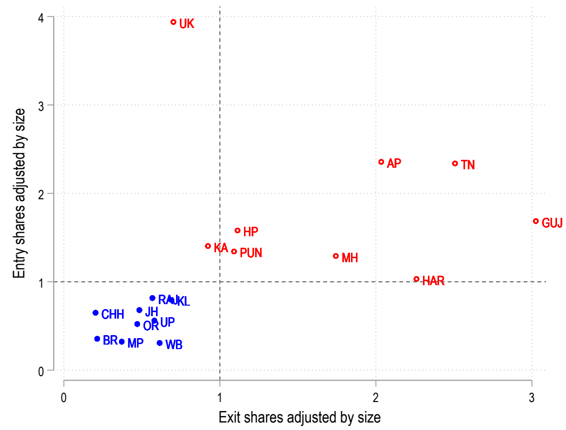
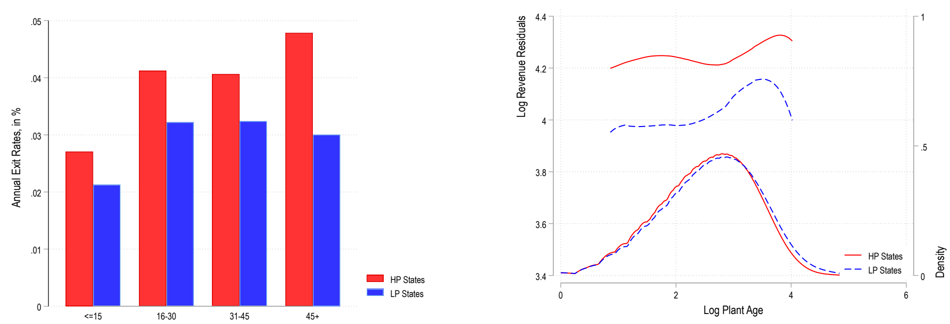


FIGURE 2.—Size-Adjusted Entry and Exit Shares Across States

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. Contiguous states of Andhra Pradesh and Telangana; Punjab and Chandigarh; Haryana and Delhi; and Karnataka and Goa have been grouped for our analyses. North-Eastern states and Jammu and Kashmir were excluded because the sample is sparse.



(a) Exit Rates in LP vs HP States

(b) Revenue Residuals versus Age

FIGURE 3.—Annual Plant Exit Rates and Revenue Residuals in High and Low-Performance States

Productivity (proxied by revenue residuals[15]) is higher for older plants in HP states but not in LP states (top of Figure 3b).

While not a focus of our analysis, it must be noted that exit rates are higher for informal manufacturing plants, presumably because they face lower institutional barriers to exit (Appendix Figure B.3).

[15]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.2 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 as a proxy for TFPQ, since TFPR can be uncorrelated with TFPQ.

***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. In this section, we show that the reform eased the exit of financially distressed and highly leveraged plants, especially when exit may have been harder to begin with—i.e., 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). The leverage ratio of a plant in any year is defined as the ratio of its liabilities to assets following Vig (2013) and Alok et al. (2022). We characterized a plant as highly leveraged if its average leverage ratio in the pre-SARFAESI period exceeded the national median. Similarly, a plant is characterized as being financially distressed if its profits in the pre-SARFAESI period are in the bottom decile of the national distribution. Finally, $\mathbb{1}\{Post_t\} = 1$ for years after the reform, i.e., starting 2002-03.

All regressions reported in Table I include plant, industry$\times$year, and state$\times$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 highly leveraged and distressed plants drive the effect, while columns 3 and 4 show that the effects mostly came from LP, not HP, states. Columns 5-7 repeat models 2-4 but also include a high-leverage $\times$ year fixed-effect to account for differential trends among highly leveraged plants and show that our results are robust.

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

This section shows that plants in LP states adjust labor less in response to similar economic shocks, indicating higher labor adjustment costs relative to high-performance states. We follow Guiso et al. (2005) to isolate unanticipated changes in gross value added (GVA)

TABLE I

THE EFFECT OF BANKRUPTCY REFORMS ON EXIT RATES

	(1)	(2)	(3)	(4) $\mathbb{1}\{Exit_{ijst}\}$	(5)	(6)	(7)
$\mathbb{1}\{Post_t\} \times \mathbb{1}\{HighLeverage_i\}$	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.

that cannot be explained by plant-specific characteristics and aggregate fluctuations. In particular, we regress the inverse sine transformation of gross value-added (GVA)[16] on a plant (λ_i), an industry-year (λ_{jt}), and a state-year (λ_{st}) fixed effect. The regression residuals, r_{ijst}, capture the unanticipated shocks to a plant's GVA.

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

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

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 a rich set of covariates that are both time-invariant and time-varying in

[16]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.

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 HP states. β_2 captures the differential response to negative shocks in LP 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 II

IMPACT OF NEGATIVE SHOCKS ON EMPLOYMENT IN HIGH AND LOW-PERFORMANCE STATES

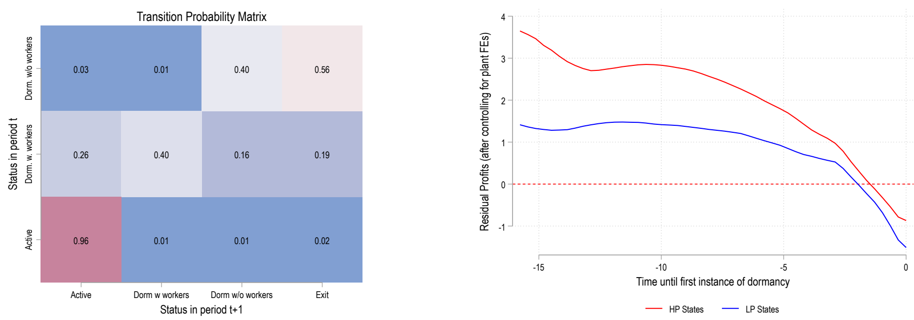
Dependent variable:	log Employment					
	(1) Regular Workers	(2) Regular Workers	(3) Contract Workers	(4) Contract Workers	(5) Managers	(6) Managers
$\mathbb{1}\{Shock_{it-1}\}$	-0.086***	-0.091***	-0.122***	-0.122***	-0.081***	-0.083***
	(0.003)	(0.004)	(0.009)	(0.011)	(0.003)	(0.004)
$\mathbb{1}\{Shock_{it-1}\} \times \mathbb{1}\{LP_s\}$		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.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Column 1 of Table II 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 LP 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 LP states, compared to 9.1% in HP 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 HP and LP states adjust their contract and managerial employment in response to negative shocks. This makes sense as the labor laws protect regular workers, not contract workers or managers.

Next, we show that the labor adjustment frictions in LP states are driven by larger plants, consistent with the labor laws making firing particularly hard for plants employing more than a hundred workers. We define $\mathbb{1}\{Above100_{it-1}\} = 1$ for plants with more than 100 regular workers in year $t-1$. Then, we estimate a triple differences (saturated) version of the model (1). Columns 1 and 2 of Appendix Table B.1 show that 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. Columns 3 and 4 of Table B.1 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.*



(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}). We use data only on census sector plants (>100 workers) from 1999-2007 and classify a plant as having exited if it disappeared from the panel and then doesn't reappear until 2018. We aim to be conservative, and truncating the sample in 2007 ensures that a plant does not appear in the sample for at least 11 years to be classified as having exited. 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.

Establishments may choose to be dormant either in response to a temporary shock or because they want to exit but can't. In this section, we show that the dormancy status recorded in the data is consistent with many of these plants being distressed, i.e., making consistent losses and on a path to exit, like Nokia's Indian factory. Figure 4a shows the transition probabilities of plants between the different statuses. 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 restart soon. However, a large fraction of them either continue to stay dormant with workers or transition to laying off workers and finally exit. However, after entering dormancy without workers, the plant is unlikely ever to restart production. Based on these transition probabilities, we postulate that dormancy is a path to exit for plants.

To be sure that the plants entering dormancy are, on average, economically distressed, Figure 4b plots the profits of active plants as they approach dormancy. 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.

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 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.

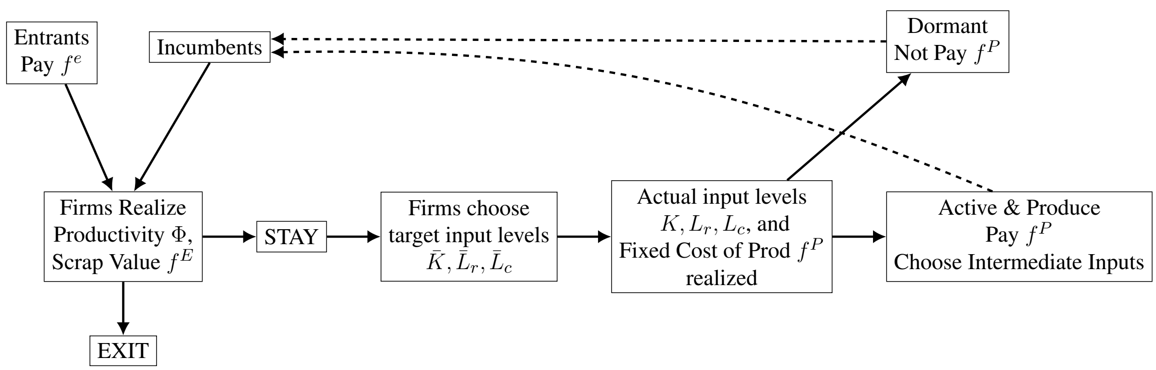


FIGURE 5.—Timing of Events

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}).[17] 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.

[17] 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.

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 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[18], 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.[19] 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,

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

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

$\tilde{\phi}_{it} = \Gamma \left(E^{\frac{1}{\sigma-1}} \phi_{it} \right)^{\frac{\frac{\sigma-1}{\sigma}}{1-\alpha_I \frac{\sigma-1}{\sigma}}}$. 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 $\left(\bar{L}\right)$ and employment in the 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:[20]

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

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.

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

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[21] 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:

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

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.

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

[21] 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.

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_K^{ε}.

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_{FK}^E. Hence, upon exiting, firms get their realized scrap value, plus the value of the sale of undepreciated capital,[22] net of adjustment costs incurred, denoted by $\tilde{f}^E$. Hence:

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

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_f^E 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 $\bar{K}$.[23] 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 the Appendix, we explore how sensitive our counterfactuals will be to raising the capital supply elasticity upwards from zero.

[22] We denote the undepreciated part of capital with δ^K. So the capital depreciation rate is $1 - \delta^K$

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

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.

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,

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

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 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

$S_{t-1} = D$.[24]

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

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:

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

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.

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

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, $\sigma^{\varepsilon}_{Lr}$, $\sigma^{\varepsilon}_{Lc}$), 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 ($\tilde{\gamma}_0$, $\tilde{\gamma}_1$, $\tilde{\sigma}^{\varepsilon}_{\gamma}$).

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

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.,

$$\theta = \{\tilde{\gamma}_0, \tilde{\gamma}_1, \tilde{\sigma}_{\gamma}^{\varepsilon}, c_{Hc}, c_{Fc}, c_{Hr}, c_{Fr}^L, c_{Fr}^S, c_{HK}, c_{FK}, \sigma_{Lc}^{\varepsilon}, \sigma_{Lr}^{\varepsilon}, \sigma_K^{\varepsilon}, \mu_f^{PP}, \mu_f^{DP}, \sigma_P, c_{FK}^E, \mu_f^E, \sigma_E\}$$

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.[25] 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*

We use indirect inference to estimate our dynamic model as is common in dynamic models. We specify an auxiliary model that can pin down the structural parameters. Let θ^a denote the parameter vector of the auxiliary model, and θ the corresponding one for the structural model. We use hats to indicate their estimated values. Our approach has two

[25]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.

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 $S(\theta^a, data)$, which depends on θ^a and the 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, 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.

In our setup, firms face discrete (active, dormant, exit) and continuous choices (how much labor and capital to employ). In this 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 be concrete, we simulate 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.

There is a final problem, namely that we have holes (missing data) in the Annual Survey of Industries 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.[26] From this information and the assumption of independence between be-

[26]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. We assume a polynomial function form of capital and employment, conditional on the production/dormancy status in the previous year as well as state and year dummies, when estimating the missing probability.

ing missing and exiting, we can back out the probability of exit.[27] 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.[28]

6.2. *Identification*

We now discuss the intuition behind the identification of the key parameters in the model. We start with the means and variances of the fixed production cost shocks $\left(\mu_f^{PP}, \mu_f^{DP}, \sigma_P^2\right)$, and the parameters governing the scrap value distribution $\left(\mu_f^{E}, \sigma_E^2\right)$.[29] 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 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.

[27]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.

[28]Details regarding our estimation procedure are in Appendix D.

[29]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

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 ($\sigma^{\varepsilon}_{Lc}$, $\sigma^{\varepsilon}_{Lr}$). 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 $\tilde{\gamma}_0$, $\tilde{\gamma}_1$, $\sigma^{\varepsilon}_{\gamma}$. 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.[30] Once θ is estimated, we solve out the entry cost f^e such that firms have zero expected profits by entering the market.

6.3. *Estimates of Structural Parameters*

We begin with the 9 parameters that we calibrate. These are reported in Table III. 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.[31] We set the discount factor δ^V to 0.9 and the capital depreciation rate, $(1-\delta^K)$, to 0.1. 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).

The structurally estimated parameters are reported in Table IV. 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

[30] 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.

[31] 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 III

CALIBRATED PARAMETERS

Panel 1: Common		Panel 2: Labor and Capital Intensive Sectors			Panel 3: High- and Low-performance States		
δ^V	0.9		Labor	Capital		HP States	LP States
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			

TABLE IV

PARAMETER ESTIMATES

	HP	LP		HP	LP
Panel 1: Profitability Process			Panel 5: Adjustment Cost of Non-regular Workers		
$\tilde{\gamma}_0$	0.189 (0.0043)	0.184 (0.0033)	c_{Hc}	29.443 (0.8774)	
$\tilde{\gamma}_1$	0.89 (0.001)		c_{Fc}	36.18 (17.95)	34.71 (3.72)
$\sigma^{\varepsilon}_{\gamma}$	0.71 (0.000478)		Panel 6: Shocks to Factor Employment		
Panel 2: Fixed Production Cost			σ^{ε}_{K}	0.38 (0.015)	
μ^{PP}_f	-21.07 (0.5460)		$\sigma^{\varepsilon}_{Lr}$	0.38 (0.0125)	
μ^{DP}_f	20.55 (0.3781)		$\sigma^{\varepsilon}_{Lc}$	0.68 (0.0138)	
σ_P	15.41 (0.3342)		Panel 7: Exit Costs		
Panel 3: Adjustment Cost of Capital			c^E_{FK}	146.88 (57.67)	
c_{HK}	237.40 (47.74)		μ^E_f	-402.64 (54.65)	-631.22 (108.58)
c_{FK}	1663.17 (286.04)		σ_E	528.50 (60.50)	
Panel 4: Adjustment Cost of Regular Workers					
c_{Hr}	94.79 (16.28)				
c^L_{Fr}	222.25 (44.49)	257.68 (120.63)			
c^S_{Fr}	171.61 (24.92)	210.74 (52.75)			

Notes: Analytical standard errors reported in parentheses.

to exit would be exit costs. Since in Panel 2, $\mu_f^{PP} < \mu_f^{DP}$, there are significant advantages to keeping the plant active.[32] Estimates on hiring and firing costs are reported in Panels 4 and 5. Note that hiring is easier than firing any type of worker, and that 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

[32]In simulations, this translates into firms paying about 1.59% of their annual value added in fixed production costs.

is usually done via a third party. Also, firing regular workers is much harder than firing contract workers. The costs are 4.7-7.4 times as much. In addition, firing regular workers is harder in low-performance states than high-performance states and harder in larger firms than smaller firms. These estimates on labor adjustment costs are consistent with the literature (e.g. Besley and Burgess, 2004, Chaurey, 2015) and with fact 3 reported 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, this is about 110.6% and 173.4% of average annual sales in high- and low-performance states, respectively. Consistent with all the empirical results reported in Section 4, these estimates imply that exit frictions are significantly greater in the low-performance states.

7. COUNTERFACTUAL EXERCISES

We will focus on the effects of various policies on productivity, value-added, firm entry and employment 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, that is, we assume that total income and the price index are fixed. We allow for feedback effects via these channels in Section 8.

In Section 7.1, we assume that capital is in fixed supply[33] 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. In Section 7.2, 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 7.3, we compare the effects of using a fixed budget to reduce entry vs. exit costs. We

[33] In Appendix C.2, we allow for an upward sloping supply of capital.

show that there is a tradeoff: entry subsidies are better for employment while exit subsidies are better for value added.

7.1. *Changing the Scrap Value and Labor Adjustment Costs*

We begin the counterfactual analysis by adjusting our policy instruments to attain 50% of the US firm exit rate, i.e., 4.5%, for India overall. Our assumption of fixed total capital supply is extremely conservative but serves as a good starting benchmark. Results are reported in Table V.

TABLE V

PARTIAL EQUILIBRIUM COUNTERFACTUALS – TARGET EXIT RATE 4.5% FOR INDIA

	Policy Instrument	Δ Value Added (%)	Δ Productivity (%)			Δ Employment (%)	Δ Mass of Firms (%)	Dormancy Length (Δ years)	Age (Δ years)
			Aggregate	Entrants	Exiters				
1	Exit Cost	14.27	3.23	-1.73	5.54	8.08	17.98	-0.57	-2.87
2	Labor Adj Cost	16.38	3.85	-1.25	5.51	-14.56	19.81	-0.58	-2.86

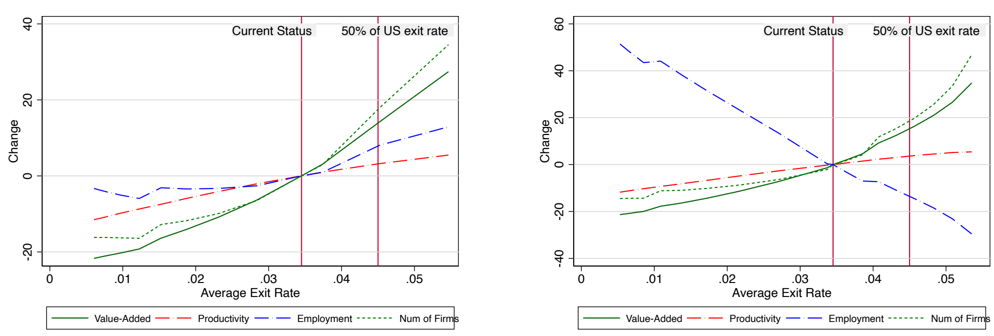
Note: This table presents counterfactual estimates of various aggregate outcomes of interests, that result from changing one of two policy instruments: exit costs (rows 1) or labor adjustment costs (rows 2). To obtain aggregate outcomes or exit rates, each of the four categories is weighted by the mass of the firms in the pooled data. This corresponds to results plotted in Figure 6.

The first instrument we consider is raising the mean of the scrap value distribution by the same nominal amount for each industry$\times$state group such that the all-India exit rate equals 4.5%. This is equivalent to giving a fixed exit subsidy to each firm that chooses to exit. An increase in the mean scrap value results in low-productivity firms that do not have very high employment (since firing costs have not fallen) exiting. This raises the average productivity of exiters, as well as productivity overall, and reduces 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.

With the targeted exit rate at 4.5%, the average value added and firm mass in manufacturing increase by 14.27% and 17.98%, respectively. Employment rises by 8.08%. Productivity rises by 3.23%. The avg. productivity among firms that exit increases by 5.54% while that of entrants falls by about 1.73%, and the average time firms spend in dormancy goes down by 0.57 years.

Next, we turn to lowering labor firing costs by a common fraction for all sub-groups to achieve the target exit rate for India overall. These results are reported in row 2 of Table V. Quantitatively, the change in value-added is 16.38%, in the mass of firms is 19.81%, and in productivity is 3.85%. These are not very different from increasing the mean scrap value. Note that the changes in dormancy length and age are almost the same. The big difference is that when we reduce firing costs, employment in manufacturing falls by 14.56%. 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.

Appendix Table C.2 discusses the outcomes for each sub-group from the above experiments. Results from an alternative experiment with different subsidies/labor cost reductions in each sub-group so that each one attains an exit rate of 4.5% are reported in Appendix Table C.3. Finally, we explore the role of capital supply elasticity in Appendix C.2.



(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 of interests as a result of changing policy. The figure plots the counterfactual average exit rates on the x-axis, while the corresponding outcomes are on the y-axis. To obtain aggregate outcomes and exit rates, each of the four categories is weighted by the mass of the firms in the pooled data.

What happens when the targeted rate varies? These results are presented graphically in Figure 6. 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.[34] Panel (a) of Figure 6 presents the results for changing scrap value, while Panel (b) depicts the effects of changing labor adjustment cost. Note that both policy changes monotonically affect each of the variables. The big difference in the two panels is the effect on the employment, which rises in Panel (a) and falls in (b). Also note that the number of firms increases more steeply than does value added, as the entrants get less productive, and exiters get more productive.

7.2. *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.

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

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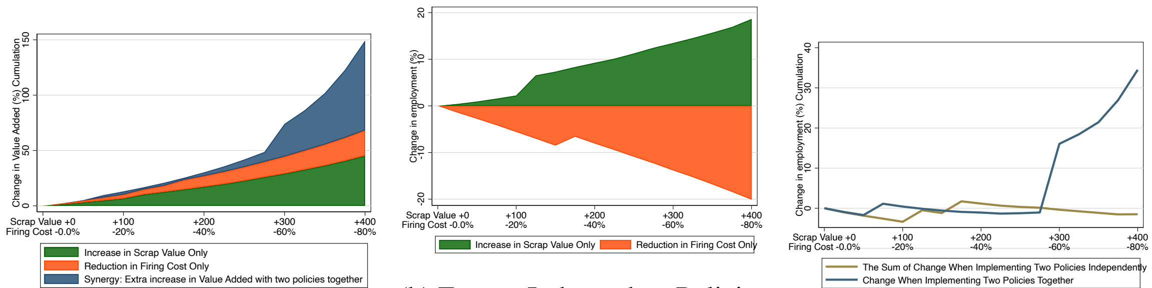
[34] In order to see the variation in our four subgroups, we present the effects for each of them separately in Appendix C.1.



(a) Value Added

(b) Emp. – Independent Policies

(c) Emp. – Joint Policies

FIGURE 7.—Synergies in Policies

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.

7.3. *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.

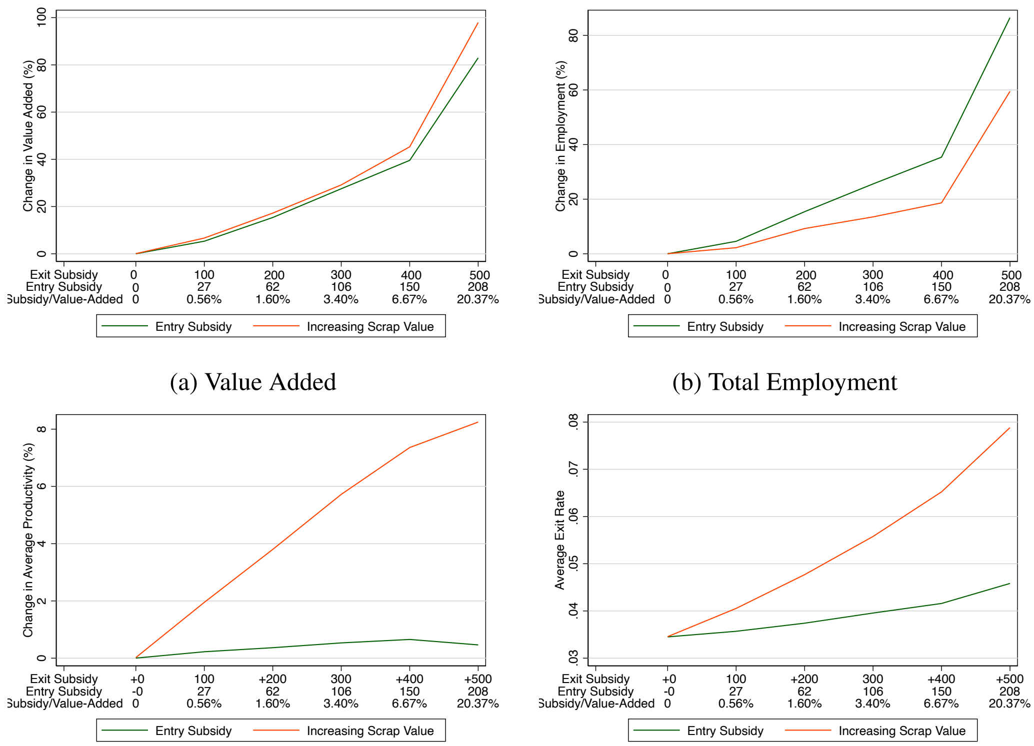
It is clear from Figure 8a that reducing exit costs has a much higher effect on value-added than reducing entry costs for a given budget, and more so for higher budgets. There are three forces at work. First, an increase in the mass of entrants raises value added by definition. Second, an increase in 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.

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.[35]

[35]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.



(a) Value Added (b) Total Employment

(c) Average Productivity (d) Exit Rate

FIGURE 8.—Subsidies to Entrants vs Reduction in Exit Cost

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}.[36] $\tau_{ld} = 1$ 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[37], 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.[38] However,

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

[37]$k =$ Labor- or Capital- intensive sectors.

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

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 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).

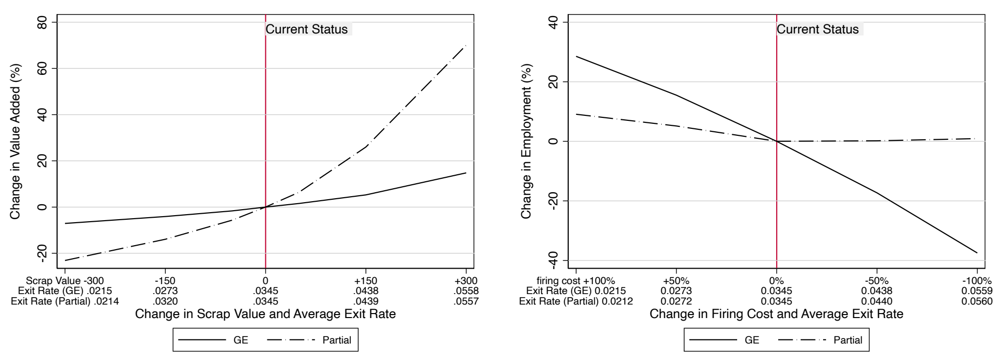
$$VA_{kl}(\phi_t, L_{c,t}, L_{r,t}, K_t) = \Gamma \left(\phi_t L_t^{\alpha_L} K_t^{\alpha_K}\right)^{\frac{\frac{\sigma-1}{\sigma}}{1-\alpha_I \frac{\sigma-1}{\sigma}}} \left(\sum_d \tau_{ld}^{1-\sigma} \frac{\beta_k E_d}{P_{k,d}^{1-\sigma}}\right)^{\frac{\frac{1}{\sigma}}{1-\alpha_I \frac{\sigma-1}{\sigma}}}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

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.[39]. The GE counterfactuals are performed using the methodology for the "Aggregate India" row of Table V. 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.



(a) Effects of changing scrap value

(b) Effects of changing labor adjustment costs

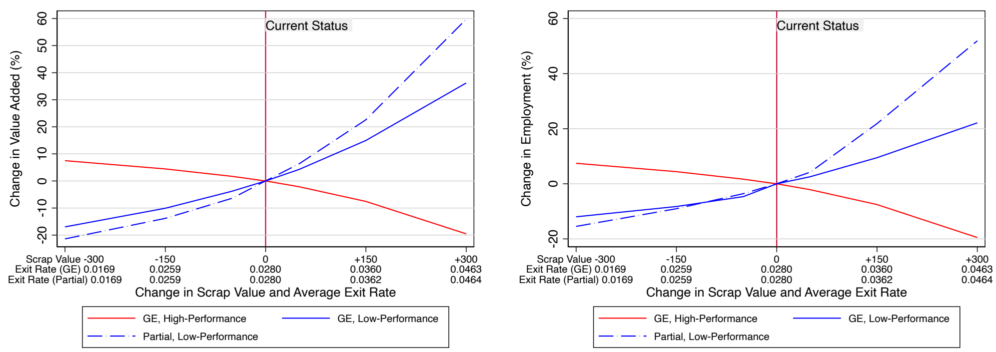
FIGURE 9.—General vs. Partial Equilibrium Counterfactuals with capital supply elasticity 0.75

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.6, 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.7. 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

[39]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).

policy change in PE are 20% vs around zero in GE (see Panel (b) in Figure C.6). 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.[40] 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: 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*.[41]



(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

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

[41]Compare the three LHS and three RHS panels of Figure C.6 and C.7.

considerable spillovers across sectors, in particular to services (e.g., Fan et al., 2023). This would suggest that our estimated effects are very conservative, as we do not allow for such interactions.

9. CONCLUSION

Governments routinely deploy policies aimed at attracting firms, stimulating employment, and promoting development—typically through tax breaks or various forms of subsidies. Yet governments have a poor record of "picking winners," and efforts to lure multinationals through tax holidays or subsidies often end up merely enriching firms that relocate once incentives lapse (Bond (1981)).

This paper shifts the focus from *entry* promotion to *exit* regulation and shows that exit barriers are as critical as entry barriers for growth and development. Reducing exit costs primarily targets firms that ought to leave the market but remain because of high firing costs or low scrap values. Such barriers trap productive resources inside low-productivity firms, depressing aggregate productivity. Moreover, because exit costs also act as entry barriers, they deter entry, further slowing down growth. As demonstrated in Section 7.3, devoting the same fiscal resources to lowering exit barriers generates substantially larger gains in value added and markedly higher productivity—albeit with smaller short-run employment effects—than equivalent spending on entry subsidies.

Exit costs matter in all economies. In advanced economies such as the United States, they appear mainly as bankruptcy costs, whereas in developing countries they take on many additional forms. Indian policymakers have acknowledged this imbalance. The Government of India's 2015–16 Economic Survey noted 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."* Yet, little guidance exists on the likely effects of exit-oriented reforms, the heterogeneity of impacts across industries and regions, or the complementarities among different reforms.

This paper provides such guidance by quantifying the consequences of high exit costs and by showing how reducing them reshapes firm dynamics, resource allocation, and aggregate performance.

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Online Appendix Material for

No Country for Dying Firms: Evidence from India

by Shoumitro Chatterjee, Kala Krishna,
Kalyani Padmakumar, and Yingyan Zhao

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FOR ONLINE PUBLICATION

APPENDIX A: INSTITUTIONAL HISTORY

A.1. *Labor Laws, Hiring, and Firing Labor*

Labor laws in India are complex, overlapping, and often ambiguous in their implementation. While the Industrial Disputes Act (IDA) of 1947 is central to regulating employment termination, it is only one part of a sprawling legal framework whose origins predate independence. The Factories Act (1922), Mines Act (1922), Workmen's Compensation Act (1923), Trade Unions Act (1926), and Trade Disputes Act (1929) were all enacted during colonial rule and continue to shape industrial relations today.

As labor is a subject on the concurrent list,[42] both central and state governments may enact labor laws. This has led to substantial legal proliferation. Maharashtra, for example, lists 48 applicable labor laws,[43] West Bengal 31,[44], and Telangana 47. The IDA itself has been amended multiple times, but differently across states (Besley and Burgess 2004).

Importantly, the statutory text alone does not determine labor market outcomes. Implementation frequently diverges from legal provisions, and enforcement remains discretionary. One key example is the IDA's requirement for government approval before retrenchment. Until recently, firms with more than 100 workers had to obtain prior permission; post-2021 amendments raised this threshold to 300. In practice, permission is rarely granted and the process lacks transparency, deterring formal exits and reinforcing informality. The discretion vested in bureaucrats leads to unpredictable outcomes.

A second institutional constraint arises from judicial backlog and procedural delays. With just one labor court per 500,000 workers, courts are overburdened. As of October 2020, over 100,000 labor cases were pending—35% for over a year, and 37% of those for more than three years.[45] The Union Labour Minister identified frequent adjournments, absenteeism of parties, and parallel challenges in higher courts as major causes. Rao (2019) documents sharp variation across states in court efficiency, indicating that the practical burden of dismissal disputes is highly location-dependent.

[42] The Indian Constitution divides legislation into central, state, and concurrent lists. Labor, internal trade, and commerce fall under the concurrent list, enabling both Parliament and state legislatures to legislate.

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

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

[45] Sundar (2020); Teamlease Services (2006).

More fundamentally, India's labor regime is shaped by common law principles that evolve through judicial interpretation. While statutes have remained relatively stable, courts have frequently redefined key terms, contributing to regulatory uncertainty. Sarkar (2019) documents how courts' reading of labor law has changed in tandem with broader ideological shifts—from a pro-worker bias during India's socialist decades to more pro-employer interpretations in the liberalization era. Yet even within a short time span, rulings on near-identical cases can diverge significantly, as shown in Kaul (2020).

A central ambiguity is the scope of the IDA: what constitutes an "industry," and who counts as a "workman"? These definitions govern whether an employment termination qualifies as "retrenchment," requiring procedural safeguards.

The definition of "industry" has evolved substantially. In Hospital Mazdoor Sabha v. State of Bombay (1960),[46] initially, the Bombay High Court had dismissed the petition of the ward servants of JJ Hospitals for retrenchment compensation. Later, the Supreme Court held that hospital services constituted an "industry" since they provided systematic services via hired labor. But in Safdurjung Hospital v. Kuldeep Singh (1967),[47] the Supreme Court reached the opposite conclusion, stating that state-run hospitals were non-commercial and therefore not industries. Subsequent rulings expanded the term to cover a wide range of economic activities even in the absence of profit, bringing philanthropies, educational institutions, and utilities under the IDA.

The definition of "workman" has also been inconsistently applied. The IDA covers those employed to perform manual or clerical work, excluding supervisors and managerial staff. Yet the Court has repeatedly struggled to draw clear lines. In Shivnandan Sharma v. Punjab National Bank (1955),[48] the Court ruled that a cashier appointed by an external contractor was still a workman under the bank's control. Similarly, in the beedi industry, courts have issued conflicting rulings. In Birdhichand Sharma v. First Civil Judge, Nagpur (1961),[49] factory-based beedi rollers were deemed workmen due to the firm's control over attendance and quality. But the Court held otherwise in Shankar Balaji Waje v. State of Maharashtra

[46] AIR 1960 SC 610.

[47] (1970) 1 SCC 735.

[48] AIR 1955 SC 404.

[49] AIR 1961 SC 644.

(1962),[50] where a worker was not bound to attend the factory. The dissenting judge, however, emphasized that managerial oversight—even via quality control—was sufficient to establish an employer-employee relationship. That view eventually informed later rulings, such as Mohideen Sahib Sons v. Industrial Tribunal, Madras (1966).[51]

The Supreme Court has also reversed itself on whether professional employees can be "workmen." In a series of judgments in the 1960s,[52] the Court excluded employees not engaged in manual, clerical, supervisory, or technical work. But in the 1980s,[53] it broadened the interpretation, ruling that designation alone is insufficient to deny IDA protection if the nature of the work fits statutory criteria.

These ambiguities have practical consequences. Interviews with HR managers in Indian tech and industrial firms confirm that the outcomes of labor disputes are highly uncertain once they reach the courts. Larger firms frequently preempt litigation by offering high severance payments. Smaller or distressed firms, lacking this flexibility, face greater exposure to the risks and costs of prolonged adjudication.

In sum, India's labor regime imposes not just legal constraints but legal ambiguity. While much research has focused on de jure rigidity (e.g., IDA thresholds), it is the uncertainty in interpretation, inconsistent enforcement, and procedural delays that often shape firm behavior. These frictions raise effective adjustment costs and may help explain the persistence of informality, low exit rates, and limited employment dynamism despite reforms.

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[51] AIR 1966 SC 370.

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

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

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A.2. *Bankruptcy Laws*

Unsurprisingly, India's bankruptcy laws were derived from English laws. 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 the early 1800s. 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 1990s, governments have attempted various reforms with limited success.

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. Technically, courts should not intervene once a bank starts recovery proceedings under the SARFAESI Act. However, High Courts often stay recovery proceedings, requiring intervention by the Supreme Court and delaying the process.[54] Other issues with SARFESI include the absence of clear guidelines on which creditor gets paid first when a firm defaults. Courts also

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

do not have the expertise to distinguish between viable and non-viable firms. They usually follow a pro-debtor stance, and they are reluctant to order the liquidation of non-viable businesses (Ravi 2015; BLRC Report, 2015). 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. However, even the IBC has minimal success due to several judicial bottlenecks and court congestion[55]. Despite these issues, there is little work on the extent of exit barriers, how they vary across states, and the effect they seem to have on firms, firm dynamics, and productivity in India.

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APPENDIX B: ADDITIONAL DATA FACTS

B.1. *Details about exit calculations*

- *All-India exit rate for formal manufacturing from ASI data* (Used in Figure 1a):

  Using data from years 2001 and 2016, we group plants into cohorts c based on their age in 2001. For each cohort c, we compute plant mass in 2001 (M_c^{2001}) and 2016 (M_c^{2016}), and calculate the annual exit rate δ_c from $M_c^{2016} = (1 - \delta_c)^{15} M_c^{2001}$.

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

All-India exit rate is then the weighted average of cohort-wise exit rates (δ_c's), with weights being the share of plants in each cohort as of 2001.

- *All-India exit rate for informal manufacturing from NSS data* (Used in Figure 1b):

  We follow the above steps for years 1994-95 and 2015-16. While computing cohort-wise exit rates, we modify the formula to account for the 21-year gap between 1994-95 and 2015-16.

- *Exit rates by age cohort for HP/LP states from ASI data* (Used in Fig 3a):

  For each state group (HP/LP states), we follow the steps outlined above to compute cohort-wise exit rates.

- *State-wise exit shares from ASI data* (Used in Fig 2):

  Using data from years 2001 and 2016, we group plants into cohorts c based on their age in 2001. For each cohort c, we compute the all-India plant mass in 2016 (M_c^{2016}) and 2001 (M_c^{2001}), as well as plant mass in state s in 2016 (M_{cs}^{2016}) and 2001 (M_{cs}^{2001}). The annual exit share for cohort c in state s is: $\delta_{cs} = \frac{M_{cs}^{2001} - M_{cs}^{2016}}{M_c^{2001} - M_c^{2016}}$.

  State-wise exit share is then the weighted average of δ_{cs}, with weights being the share of plants in cohort c in state s in 2001.

- *Plant-level exit from ASI data* (Used in Fig 4a and Table I):

  Using the sample from 1999-2018, we identify the last year each plant appears in the dataset. For plant i, let the last year be T_i. Plant 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 plant does not re-appear.

- *Firm-level exit from Prowess data* (Used in Fig 1b):

  Using data 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 ensure the firm does not reappear.

B.2. *Entry Shares versus Misallocation*

Do entry shares correlate with the extent of resource misallocation across states? To examine this, we measure misallocation using the elasticity of plant size with respect to plant-level revenue residuals, following Lucas (1978) and Bento and Restuccia (2021).

We define plant size as the number of non-managerial workers employed. As noted in Foster et al. (2016), plant-level revenue residuals (i.e., residuals from the plants' revenue function) capture plant-level productivity and demand shocks, and crucially, do not include plant-level prices. To see this, consider the following setting. Suppose plant output follows $Y = \phi L^{\alpha_L} I^{\alpha_I} K^{\alpha_K}$, where ϕ, L, I, and K represent productivity, labor, intermediate inputs, and capital, respectively. Additionally, let plants face the demand function $D(p) = p^{-\sigma} E$, with p as the plant-level price, σ the elasticity parameter, and E capturing aggregate expenditure and the price index. The production and demand functions imply that plant revenues are given by $R = E^{\frac{1}{\sigma}} (\phi L^{\alpha_L} I^{\alpha_I} K^{\alpha_K})^{\frac{\sigma-1}{\sigma}}$. From here, revenue residuals (RR) are defined as RR $= \frac{R}{(L^{\alpha_L} I^{\alpha_I} K^{\alpha_K})^{\frac{\sigma-1}{\sigma}}} = E^{\frac{1}{\sigma}} \phi^{\frac{\sigma-1}{\sigma}}$. Hence, revenue residuals vary across plants within an industry due to differences in TFPQ and demand shocks, and crucially, not plant-level prices or markups.[56] [57]

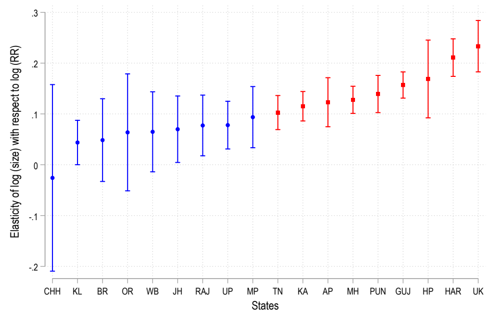
How is the elasticity between plant size and revenue residuals informative about misallocation? Intuitively, in the absence of distortions, plants with higher revenue residuals should employ more workers. Therefore, in states with fewer distortions, the elasticity of plant size with respect to revenue residuals should be higher. We interpret this measure of misallocation as a broad indicator of state-level institutional frictions, without attributing them to any particular source.

The left panel of Figure B.1 ranks states according to this measure of misallocation – states in red have lower misallocation (i.e., higher elasticities), while those in blue have higher misallocation. The right panel of figure B.1 shows that these misallocation measures

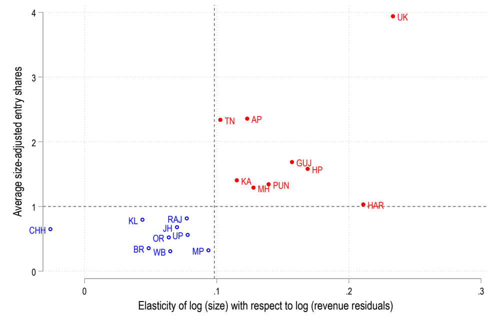
[56] It is worth noting that revenue residuals are different from total factor revenue productivity (TFPR). In the above framework, $TFPR = R/(L^{\alpha_L} I^{\alpha_I} K^{\alpha_K}) = p\phi$. In other words, TFPR is plant-level price times TFPQ. We prefer revenue residuals to TFPR as a proxy for TFPQ, since TFPR can be uncorrelated with TFPQ. For instance, in settings like Melitz (2003), high-TFPQ plants charge lower prices, leaving TFPR relatively unchanged compared to low-TFPQ plants that charge higher prices.

[57] This measure of revenue residuals also aligns with the productivity proxy in our structural model. We use $RR = R/(L^{\alpha_L} I^{\alpha_I} K^{\alpha_K})^{\frac{\sigma-1}{\sigma}}$ to compute revenue residuals, since we observe plant-level sales, L, I, and K. 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.

are correlated with entry shares – states with entry shares above 1 have lower misallocation on average, and vice versa.



(a) Misallocation Measures



(b) Entry Shares vs Misallocation

FIGURE B.1.—Correlation between state-wise misallocation measures and entry shares

Notes: 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. The right panel shows entry shares vs misallocation measures of states.
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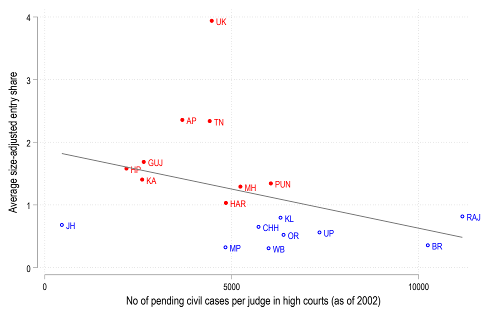
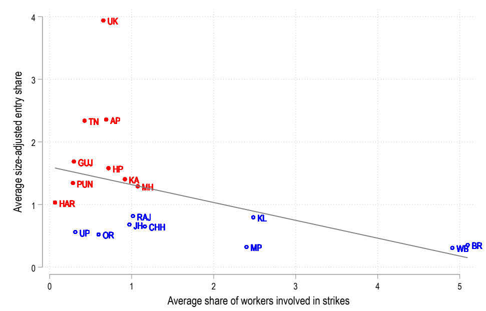
B.3. *Entry Shares versus Specific Barriers to Exit*



(a) Pending Civil Cases per Judge in High Courts

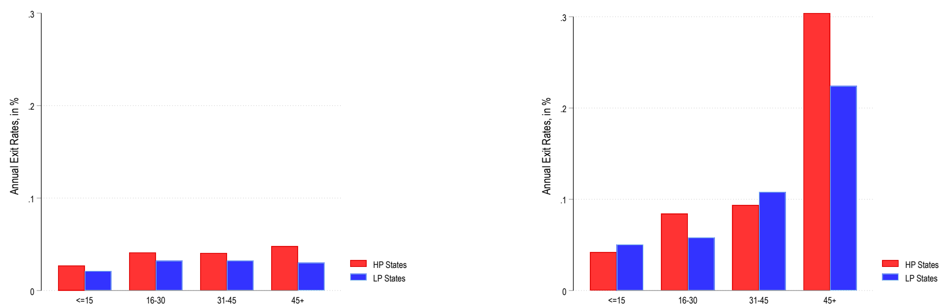


(b) Share of Workers involved in Strikes

FIGURE B.2.—Entry Shares versus Specific Barriers to Exit

Notes: Panel (a) 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. 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]. Panel (b) shows the relationship between average size-adjusted entry shares and the average share of workers involved in strikes in each state. 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 is from the 'States of India' database provided by the Center for Monitoring of the Indian Economy.

B.4. *Formal versus Informal Manufacturing Exit Rates*



(a) Formal Manufacturing

(b) Informal Manufacturing

FIGURE B.3.—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.5. *Labor Adjustment to Negative GVA Shocks*

B.5.1. *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)).

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

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.1 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.1 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.1

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
$\mathbb{1}\{Shock_{it-1}\}$	-0.093***	-0.089***	-0.122***	-0.081***
	(0.005)	(0.005)	(0.012)	(0.005)
$\mathbb{1}\{Shock_{it-1}\} \times \mathbb{1}\{LP_s\}$	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)			
$\mathbb{1}\{Shock_{it-1}\} \times \mathbb{1}\{Above100_{it-1}\}$	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)
$\mathbb{1}\{Shock_{it-1}\} \times \mathbb{1}\{LP_s\} \times \mathbb{1}\{Above100_{it-1}\}$	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.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

APPENDIX C: MORE COUNTERFACTUAL RESULTS

C.1. *Disaggregated Outcomes*

Section 7.1 discussed the aggregate effects of changing scrap value or labor adjustment cost. Table C.2 reports the results separately for each industry×state for the same policy change. i.e., targeting an overall exit rate of 4.5% by changing the scrap value or labor adjustment cost by the same amount for each sub-group.

TABLE C.2

PARTIAL EQUILIBRIUM COUNTERFACTUALS – TARGET EXIT RATE FOR OVERALL INDIA 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	-0.66	-3.25	+168.75
5		Aggregate India	3.45	14.27	3.23	-1.73	5.54	8.08	17.98	-0.57	-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	-61.88%
7		LI / LP	2.23	9.19	4.28	-1.07	3.46	-17.32	7.55	-0.70	-3.35	-61.88%
8		CI / HP	4.46	20.07	3.33	-1.34	8.00	-17.80	22.90	-0.52	-2.62	-61.88%
9		CI / LP	3.32	19.41	3.21	-1.74	7.89	-21.27	21.57	-0.69	-3.29	-61.88%
10		Aggregate India	3.45	16.38	3.85	-1.25	5.51	-14.56	19.81	-0.58	-2.86	-61.88%

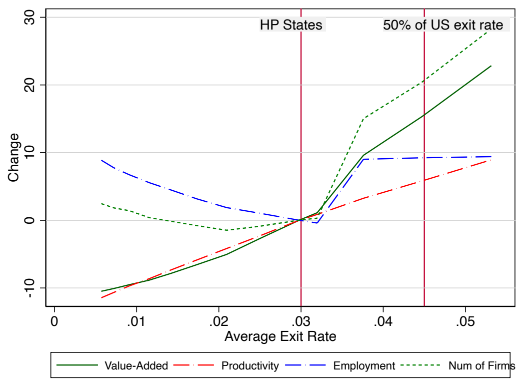
Note: This table presents counterfactual estimates of various aggregate outcomes like value added, productivity, employment, etc. that result from changing one of two policy instruments: exit costs (rows 1-5) or labor adjustment costs (rows 6-10). The data is divided into four state-industry groups as 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.

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. This is because it's base line exit rate is the lowest. So the same policy thrust achieves less. Note that in addition, even when the scrap value is raised, employment falls (slightly) in the LI/LP group, though it rises in all the other groups. As expected, entrants become less productive and exiters more productive, in each of the four groups, due to reductions in exit costs or labor adjustment costs.

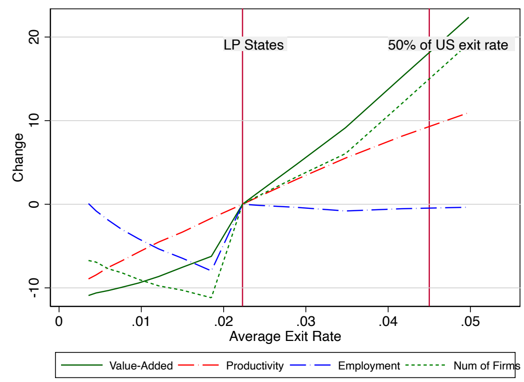
Figure C.4 and Figure C.5 present the counterfactual of policies changing exit and labor adjustment costs in four cases (Labor-intensive in High-performance states, Labor-intensive in Low-performance states, Capital-intensive in high-performance states and Capital-intensive in Low-performance states) separately. They correspond to Figure 6 in the paper but for each of the four cases seperately.

Next, we consider an alternative counterfactual experiment to understand the heterogeneity in outcomes if each industry$\times$state group achieved the same exit rate. 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$\times$state category, the policy has to be changed by a different amount to achieve the same exit rate for all categories. These results are reported in Table C.3.

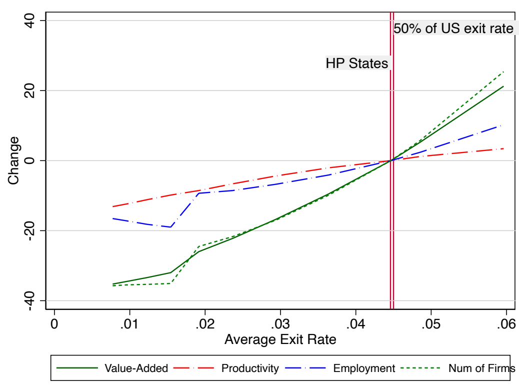
The effects of facilitating firm exit vary significantly across states and industries, depending on their initial conditions (see rows 1–4 and 6–9 of Table C.3). In capital-intensive industries located in HP states, exit rates are already close to the counterfactual target of 4.5% (i.e., 4.46%), leaving limited scope for additional adjustment. Consequently, the changes in outcome variables for this group are minimal. In contrast, labor-intensive industries in LP



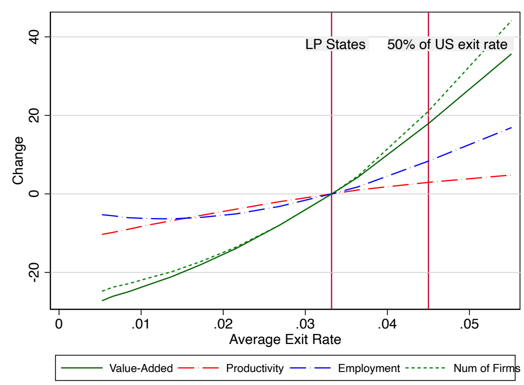
(a) LI sector in HP states



(b) LI sector in LP states



(c) CI sector in HP states



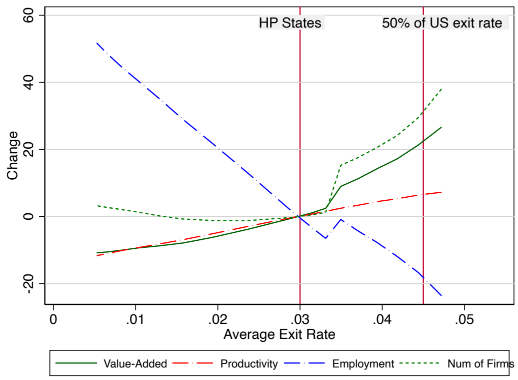
(d) CI sector in LP states

FIGURE C.4.—Counterfactual of Changing Exit Costs in Four Cases Separately

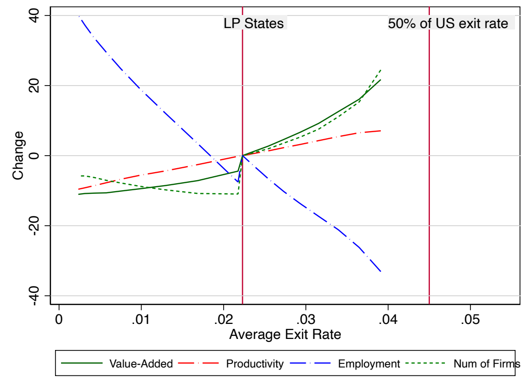
Notes: LP: Low-performance States, HP: High-performance states, LI: Labor-Intensive Industries, CI: Capital-Intensive Industries.

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 7 and 9), as firing costs here are higher and the prevalence of low-productivity firms is greater.

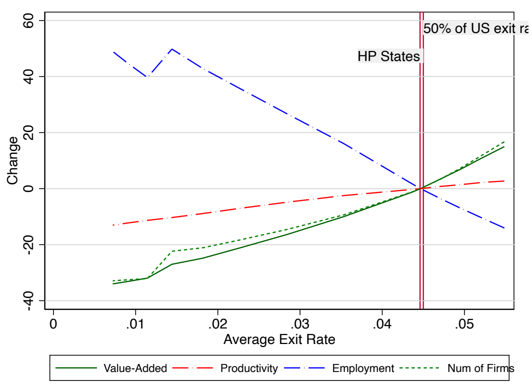
An increase in the mean scrap value leads to employment gains concentrated in the labor-intensive sector of HP states (row 1) and the capital-intensive sector of LP states (row 4). As labor adjustment costs remain unchanged, the exiting firms tend to be those with the lowest productivity rather than those with large labor forces. Consequently, fewer workers are displaced compared to a scenario involving a reduction of firing costs. It is worth noting



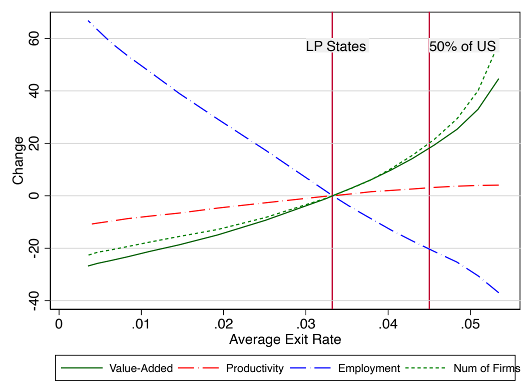
(a) LI sector in HP states



(b) LI sector in LP states



(c) CI sector in HP states



(d) CI sector in LP states

FIGURE C.5.—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.

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.

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

TABLE C.3

PARTIAL EQUILIBRIUM COUNTERFACTUALS – TARGET EXIT RATE FOR EACH GROUP 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	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	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%
7		LI / LP	2.23	21.62	7.10	-2.00	11.34	-33.08	24.31	-1.11	-5.43	-98.94%
8		CI / HP	4.46	0.49	0.08	-0.04	0.17	-0.51	0.51	-0.02	-0.08	-1.99%
9		CI / LP	3.32	18.10	2.93	-1.67	7.64	-20.37	20.13	-3.65	-3.15	-59.18%
10		Weighted Average	3.45	13.89	3.80	-1.09	5.29	-14.24	17.73	-0.99	-2.73	

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.

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% of the US exit rate in the same industries.

C.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 C.4 and Table C.5, 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.[58] 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 about 2 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.

TABLE C.4

CHANGING THE SCRAP VALUE AS IN THE BASE COUNTERFACTUAL WITH ELASTIC CAPITAL SUPPLY

Elasticity (ε_K)	Value Added (%)	Productivity (%)			Employment (%)	Mass of Firms (%)	Dormancy Length (Δ years)	Age (Δ years)
		Aggregate	Entrants	Exiters				
0	14.27	3.23	-1.73	5.54	8.08	17.98	-0.57	-2.87
0.1	16.27	3.23	-1.73	5.54	9.93	20.04	-0.57	-2.87
0.2	18.31	3.23	-1.73	5.54	11.82	22.15	-0.57	-2.87
0.5	24.72	3.23	-1.73	5.54	17.75	28.77	-0.57	-2.87
0.75	30.42	3.23	-1.73	5.54	23.02	34.65	-0.57	-2.87

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

TABLE C.5

CHANGING LABOR ADJUSTMENT COSTS AS IN THE BASE COUNTERFACTUAL WITH ELASTIC CAPITAL SUPPLY

Elasticity (ε_K)	Value Added (%)	Productivity (%)			Employment (%)	Mass of Firms (%)	Dormancy Length (Δ years)	Age (Δ years)
		Aggregate	Entrants	Exiters				
0	16.38	3.85	-1.25	5.51	-14.56	19.81	-0.58	-2.86
0.1	18.93	3.85	-1.25	5.51	-12.75	22.42	-0.58	-2.86
0.2	21.53	3.85	-1.25	5.51	-10.89	25.09	-0.58	-2.86
0.5	29.76	3.85	-1.25	5.51	-5.04	33.53	-0.58	-2.86
0.75	37.09	3.85	-1.25	5.51	0.17	41.05	-0.58	-2.86

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

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,

[58] 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.

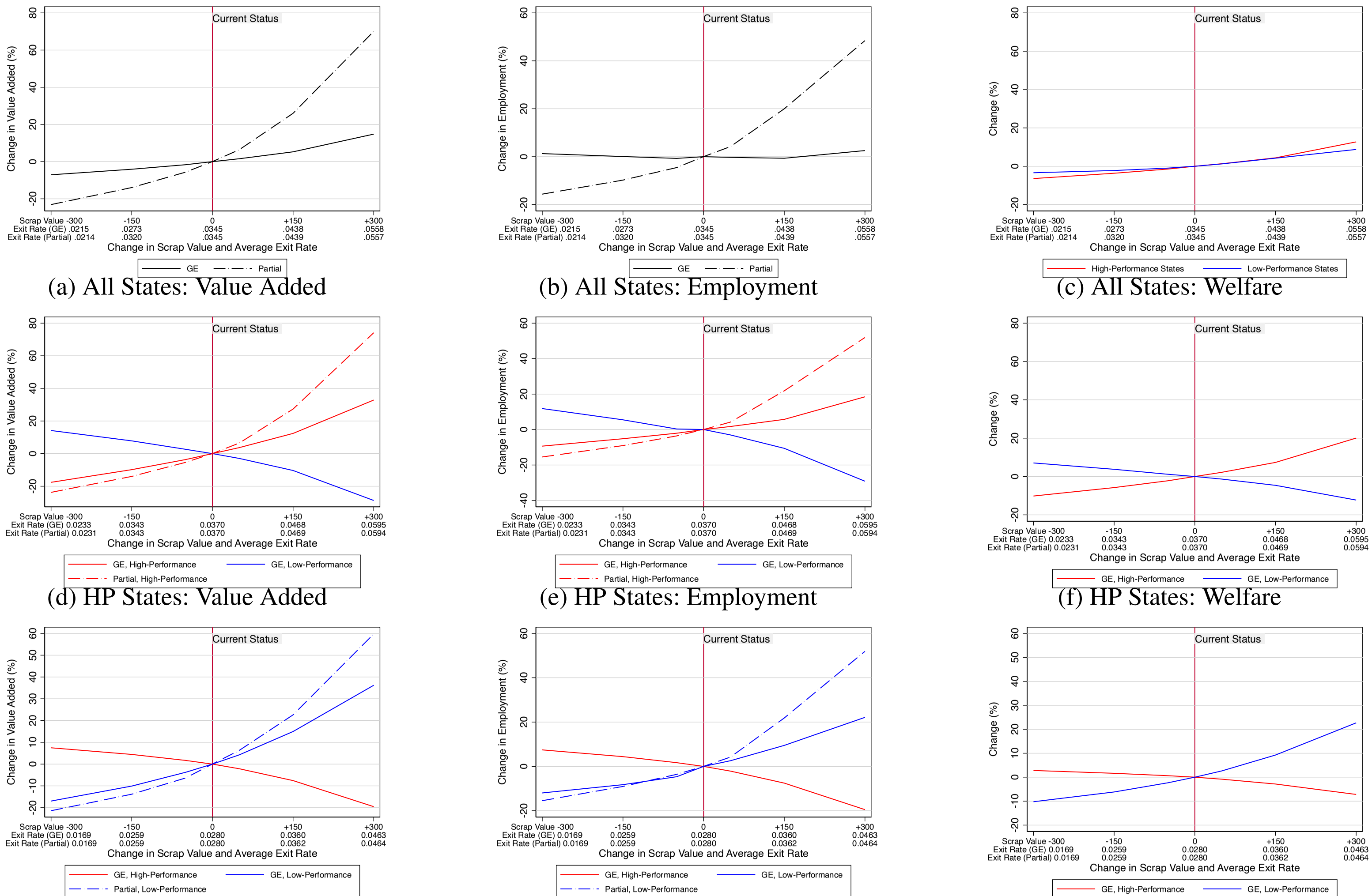
and the mass of firms are affected. Note that even with capital expanding, the employment effects of reducing firing costs remain stubbornly negative. They fall in absolute terms, from -14.56% to -5.04% when capital supply elasticity is lower than 0.5. This is due to the same selection forces being in 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 and the economy grows. 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.

C.3. *General Equilibrium Counterfactuals*

Figure C.6 and Figure C.7 have the change in the counterfactual scrap value or the change in the firing cost in percentage term on the x-axis in the first row. Below them, in the second row are the corresponding exit rates in general equilibrium. In the third row are the corresponding exit rate in partial equilibrium. For example, in Panel (a) of Figure C.6, a fall in the scrap value of 150 corresponds to an exit rate in general equilibrium of 2.73%, and in partial equilibrium of 3.20%. The y-axis presents the outcomes of interest in partial and general equilibrium.

Panels in the first column (a,d,g) in Figure C.6 depict the changes in value added. The second column (b,e,h) depict the changes in employment. The third column (c,f,i) depict the changes in welfare. The general equilibrium outcomes are given by the solid lines, and the partial equilibrium ones by the dashed ones.

Panels in the first row (a,b,c) give the outcomes for all states of changes in scrap value. All lines in this row are increasing, and general equilibrium outcomes are more muted than partial equilibrium ones.



(a) All States: Value Added

(b) All States: Employment

(c) All States: Welfare

(d) HP States: Value Added

(e) HP States: Employment

(f) HP States: Welfare

(g) LP States: Value Added

(h) LP States: Employment

(i) LP States: Welfare

FIGURE C.6.—General Equilibrium vs Partial Equilibrium: Increasing Scrap Value

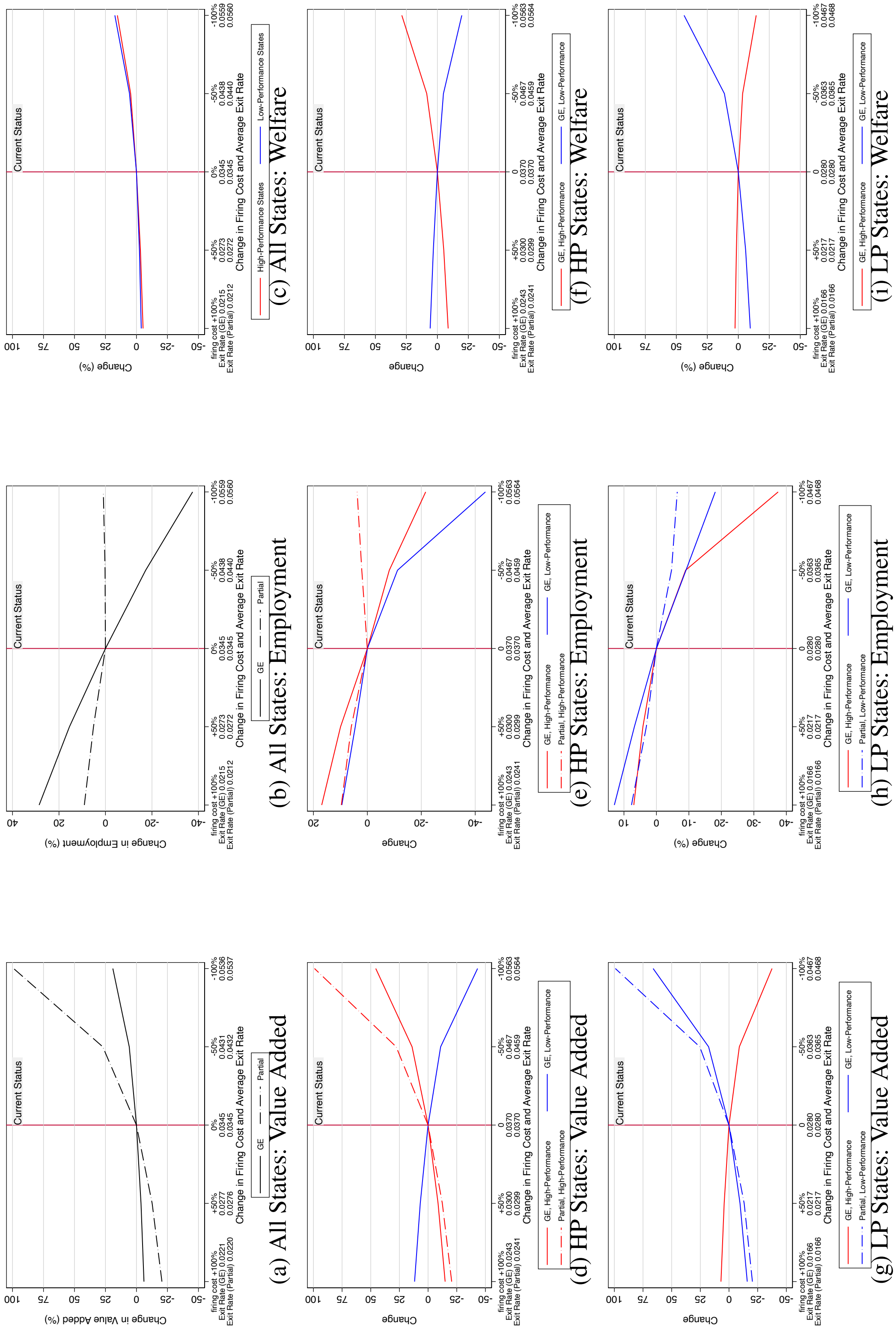


FIGURE C.7.—General Equilibrium vs Partial Equilibrium: Reducing firing cost

Panels (d), (e) and (f) depict the outcomes when only HP states reform. The red lines (dashed and solid) correspond, respectively, to the partial and general equilibrium outcomes in HP states. The blue line corresponds to the outcome in LP states under this scenario. Note that spillovers to LP states are negative so that they lose considerably in terms of all three outcomes.

Panels (g), (h) and (i) depict the outcomes when only LP states reform. The blue lines (dashed and solid) correspond, respectively, to the partial and general equilibrium outcomes in LP states. The red line corresponds to the outcome in HP states under this scenario. Note that spillovers to HP states are negative and roughly the same as the spillovers on LP states when only HP states reform.

Figure C.7 can be interpreted in an analogous manner.

APPENDIX 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.

$$\ln l_1(\theta_1^a; \tilde{\phi}_i) = \sum_{t=1}^{T} \mathbb{1}\{z_{it} = P; z_{it-1} = P\} \ln f_{\theta_1^a}(\ln \tilde{\phi}_{it} | \ln \tilde{\phi}_{it-1}) \tag{D.17}$$

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}.

$$\ln L_1(\theta_1^a; Y_{Data}) = \sum_i \ln l_1(\theta_1^a; \tilde{\phi}_i) \tag{D.18}$$

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.

$$\log l_2(\theta_2^a; \tilde{\phi}_{it}, L_{i,ct}, L_{i,rt}, K_{it}, \hat{\theta}_1^a) = \log \Pr\{VA(\tilde{\phi}_{it}, L_{i,ct}, L_{i,rt}, K_{it}) \\ -\mathbb{1}\{S_{it-1} = P\} f^{PP} - \mathbb{1}\{S_{it-1} = D\} f^{DP} > 0\} \tag{D.19}$$

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

$$\ln L_2(\theta_2^a; Y_{Data}, \hat{\theta}_1^a) = \sum_{i,t} \ln l_2(\theta_2^a; \tilde{\phi}_{it}, L_{i,ct}, L_{i,rt}, K_{it}, \hat{\theta}_1^a) \tag{D.20}$$

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

$$\ln l_3(\theta_3^a; \hat{\theta}_1^a, \hat{\theta}_2^a, Y_{Data}) \\ = \sum_{t=1}^{T} \mathbb{1}\{z_{it-1} = P\} \ln g_{(\theta_3^a; \hat{\theta}_1^a, \hat{\theta}_2^a)}(L_{i,ct}, L_{i,rt}, K_{i,t}, z_{i,t} | \hat{\tilde{\phi}}_{it}, L_{i,ct-1}, L_{i,rt-1}, K_{i,t-1}) \tag{D.21}$$

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

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

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

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

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

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,

$$\begin{aligned}
&g_{(\theta_3^a,\hat{\theta}_1^a,\hat{\theta}_2^a)}(L_{c,it}, L_{r,it}, K_{i,t}|z_{i,t}, s_{i,t}) = f_c(L_{c,it}|h_c(s_{i,t}), \sigma_{Lc}^{\varepsilon}) \cdot f_r(L_{r,it}|h_r(s_{i,t}), \sigma_{Lr}^{\varepsilon})\\
&\qquad \cdot f_K(K_{i,t}|h_K(s_{i,t}), \sigma_K^{\varepsilon})
\end{aligned}$$

where, $f_c(\cdot)$ is the pdf of a log normal distribution with mean $h_c(\cdot)$ and standard deviation σ_c^{ξ} 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.

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

Adding the likelihood components of each firm as defined in Eq (D.21) gives the likelihood function as follows

$$
\ln L_3(\theta_3^a; \hat{\theta}_1^a, \hat{\theta}_3^a), Y_{Data}) = \sum_i \ln l_3(\theta_3^a; \hat{\theta}_1^a, \hat{\theta}_2^a, Y_{Data}) \tag{D.22}
$$

We obtain the partial quasi-likelihood estimator of θ_3^a by maximizing Eq (D.22) 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.

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

Since we have discrete choices in the model, the simulated trajectories are discontinuous in the parameters. Golombek and Raknerud (2018) provides a way to smooth the objective function. The basic idea is to replace the simulated discrete choice $z_{it}^{(s)}(\theta)$ with its conditional expectation given the simulated state variables $\hat{z}_{it}^{(s)}(\theta)$. That is, $\hat{z}_{it}^{(s)}(\Theta)$ is a conditional probability of each possible state P, D, M and E.

Next, we explain how to calculate the smoothed trajectories $Y_{Sim}^{*(s)}$.

Let θ be given (We use $\hat{\theta}^{a}$ as the initial value).

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