Essays in International Economics

by

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ABSTRACT

This dissertation contains three chapters related to the study of diverse topics in international trade and economic geography. Chapter 1 focuses on how multi-establishment firms shape worker mobility and welfare by facilitating reallocation across space and sectors; Chapter 2 studies the importance of adaptation in limiting the impact of climate shocks; and Chapter 3 analyzes the impact of the the 2010 Chinese export restrictions on rare earths on US firms.

Chapter 1, titled "Sectoral and spatial reallocation via multi-establishment firms", shows how multi-establishment firms enable reallocation of workers across regions and sectors via within firm transitions. Using employer-employee matched data of Brazil, the paper shows the importance of worker movement within firms. Guided by the data, the project develops a dynamic economic geography model with multi-establishment firms, where large firms offer value to workers by reducing their mobility frictions but offer lower wages while extracting larger wage markdowns.

Chapter 2, titled "Adaptation to climate risk: Evidence from cyclones and flooding in Bangladesh", uses unique historical data on flooding and cyclone incidence in Bangladesh, and studies how individuals adapt to the increasing propensity of climate shocks by switching crops, sectors, or migrating. The project incorporates a structural model to estimate the importance of adaptation in limiting the economic cost of rising climate risk.

Chapter 3, titled "How critical are critical minerals? Firm-level Evidence from the 2010 China's Rare Earth Export Restriction", uses firm-level US census data to examine how US firms responded to China's restrictions on exports of Rare earth minerals in 2010.

CHAPTER 1

Sectoral and Spatial Reallocation via Multi-establishment Firms

Abstract

I study how large multi-establishment firms shape worker mobility and welfare by facilitating reallocation across space and sectors. Using matched employer-employee data from Brazil covering the universe of formal workers, I show that one-fourth of migration across local labor markets, and nearly 30 percent of worker transitions across industries, take place within firms. In addition, I show that multi-establishment firms mitigate the impact of negative shocks on workers, and help them exploit positive shocks, through internal reallocation. Guided by these facts, I develop a dynamic economic geography model with imperfectly competitive labor markets, in which multi-establishment firms offer lower mobility frictions but exercise labor market power. The model highlights a tradeoff: workers value the "amenity" of lower mobility frictions, but firms internalize that and offer lower wages while extracting larger wage markdowns. In the steady state calibrated to Brazilian data, multi-establishment firms offer 1.7% lower wages, with a commensurate increase in wage markdowns. However, the lower wages are largely offset by the higher option value of working in a multi-establishment firm. Finally, I show that multi-establishment firms mitigate the impact of negative local productivity shocks through internal reallocation: without them, the impact of local shocks on aggregate output would be 2-6% worse, depending on the size and the spatial scope of the shocks.

1.1 Introduction

The share of jobs in large firms (5000+ employees) in the US rose from 28 percent in 1987 to 35 percent in 2019 [Autor et al., 2020]. This pattern of large firms getting larger is not US specific. Large firms account for an increasing share of the economy in Europe [Van Reenen and Patterson,

2017], and in developing countries such as India [Kapoor, 2022]. What does the rise of large "superstar" firms mean for worker welfare?

The literature on large firms' impact on workers has largely emphasized potential negative consequences. These include evidence of higher wage markdowns at larger firms [Yeh et al., 2022, Mertens and Mottironi, 2023], the role of spatial expansion of firms in driving wage inequality [Kleinman, 2022], and the contribution of large firms to the decline in labor's share of GDP [Autor et al., 2020].

In this paper, I study a novel mechanism through which large firms could positively affect worker welfare: internal reallocation. Large firms have a distinctive feature: they have multiple establishments, operate in multiple regions within countries and participate in multiple sectors.[1] In normal times, this feature potentially offers lower mobility frictions to workers. In the face of negative shocks, this feature could allow workers to move out of declining regions or sectors by finding opportunities within the firm. Large firms could also help workers exploit positive regional or sectoral shocks by reallocating them internally. Importantly, such reallocation opportunities would be unavailable to otherwise similar workers who are employed by small firms that operate a single establishment.

I use rich employer-employee matched data from Brazil covering the universe of formal employment to study the extent of internal reallocation within multi-establishment firms. The data is ideally suited for this purpose, allowing me to follow individual workers over time and observe when they change their firm, establishment, location, or industry. Using this data, I present four facts that demonstrate the importance of multi-establishment firms in spatial and sectoral reallocation of workers.

First, multi-establishment firms do not restrict themselves to a single location (one of the 557 microregions of Brazil) or industry (one of the 564 industry classification codes). Firms with a greater number of establishments operate in more locations and more industries. On average, a firm with 10 establishments operates in 4 microregions and 3 industries. This highlights substantial heterogeneity within large multi-establishment firms, both spatially and sectorally.

Second, a large share of aggregate worker flows across locations and industries happen within the firm. Roughly 6 percent of the workers migrate every year, changing their microregion. I find that one-fourth of that migration happens with the worker staying within the same firm. Similarly, roughly 16 percent of the workers change their industry every year. I show that almost 30 percent of those cross-industry flows happen with the worker staying in the same firm. These results continue to hold for broader definitions of region and industry.

Third, working in a multi-establishment firm helps workers cope with negative shocks. I use

[1] Using data from Brazil for 2005, appendix figure A.1 shows by firm size, the average number of establishments operated, and the number of locations (microregions of Brazil) and industries in which they have activities.

the closure of a worker's establishment as a negative shock, and study whether belonging to a multi-establishment firm (as opposed to a single-establishment firm) mitigates the negative impact of closure on the worker, via reallocation to other establishments of the same firm. Given that multi and single-establishment worker characteristics might differ at the baseline, I use a triple difference specification that accounts for such differences by using multi and single-establishment workers unaffected by establishment closures, and select such unaffected workers via matching. The triple difference regression exploits variation along the following three margins: (i) multi vs single-establishment (ii) affected vs unaffected by closure and (iii) pre vs post. The triple difference estimates suggest that multi-establishment workers are 15 p.p. less likely to drop out of the labor force and 4 p.p. more likely to migrate to another microregion in the year following establishment closure. Consistent with internal reallocation driving the differential effect, I find that 25 percent of multi-establishment workers who faced an establishment closure ended up in a different establishment of the same firm.

Fourth, multi-establishment firms also help workers exploit positive shocks by reallocating them to growing sectors or locations. To do this, I leverage the boom in global commodity prices between 2002 and 2011, which was a positive sector-specific shock in Brazil. Comparing otherwise similar workers who were working in non-commodity sectors in 2002, I find that working in a firm that had a commodity establishment in 2002 increased the probability of entering the commodity sector 5 years later by 5.5 p.p.. The existence of activities in the commodity sector within their firm thus facilitated the movement of workers to the sector. While workers could join the commodity sector both within and outside the firm, I find that at least 84% of the differential effect is explained by transitions that occurred within the firm.[2]

The above facts highlight how large multi-establishment firms shape labor mobility and worker welfare through internal reallocation. At the same time, the presence of large firms in the economy raises concerns about labor market power. Indeed, recent work shows not only that larger firms have higher wage markdowns [Mertens and Mottironi, 2023], but that multi-establishment firms have higher markdowns, even conditional on firm size [Yeh et al., 2022]. To evaluate the quantitative impact of multi-establishment firms on labor reallocation, monopsony power and worker welfare, I develop a dynamic economic geography model that builds on Caliendo et al. [2019] in two directions. First, to speak to internal reallocation, the model features both multi and single establishment firms. Second, to discuss potential implications for labor market power, I assume that firms compete in a labor market characterized by Bertrand competition.

In the model, workers are homogeneous, draw idiosyncratic preferences across establishments in the economy every period, and choose the establishment that offers them the highest utility. Es-

[2] 84% is a lower bound, as workers could have transitioned to the commodity sector within their firm, and then moved to another firm while staying in the commodity sector.

tablishments differ from each other based on their sectoral affiliation, their location and the number of establishments in their firm. Importantly, there is a firm switching friction, which implies that moving to an establishment within the firm is easier than moving to an establishment outside the firm. In this environment, multi-establishment firms offer workers the amenity of lower mobility frictions. At the same time, Bertrand competition in the labor market allows multi-establishment firms to internalize the value of the amenity they offer via higher wage markdowns. The Bertrand setting allows for a microfoundation of the empirical finding that shows multi-establishment firms have larger wage markdowns than single-establishment firms, even after controlling for firm size [Yeh et al., 2022].[3]

My model brings together two areas in the literature. It adds to dynamic economic geography models [Artuç et al., 2010, Caliendo et al., 2019] by introducing imperfect labor markets, and adapts the models of imperfect labor markets [Berger et al., 2022, Felix, 2021] to a dynamic setting, instead of a static one. As in Berger et al. [2022] and Felix [2021], markdown at the establishment level is a function of labor supply elasticity and a measure of the market share of the establishment in the labor market. Differently from Berger et al. [2022], the measure of market share depends on the transition rates of workers from all other establishments in the economy to the relevant establishment, and is given by the components of the establishment level transition matrix. The formula for wage markdown that I derive encompasses as limiting cases monopsonistic competition and perfect competition in the labor market.

I calibrate the model to match key moments in the data, such as the share of employment in multi-establishment firms, the share of workers that migrate or change sectors every year, and importantly, the share of migration and sectoral reallocation that happens within the firm. The steady state of the model allows me to quantify the importance of two key ideas. First, on average, multi-establishment firms are able to extract a 1.5% larger wage markdown, and get away with offering 1.7% lower wages relative to single-establishment firms.[4] This effect comes from firms internalizing the "amenity" value of being multi-establishment, and increases with the number of establishments in the firm. The 1.5% larger markdown explains roughly 10% of the difference between markdown of multi and single-establishment firms found in the literature (see Yeh et al. [2022]). Second, while wages of multi-establishment firms are 1.7% lower on average relative to single-establishment firms, I find that the "amenity" value of lower mobility frictions offered by multi-establishment firms compensates for 70% of the lost wages.

The steady state analysis misses an important feature of multi-establishment firms: their ability

[3]Note that this would not be possible in a setting where the labor market is characterized by perfect competition or monopsonistic competition. For example, under perfect competition, firms would pass through the amenity value fully to lower output prices.

[4]Prices account for the difference between larger markdown and lower wage: prices of multi-establishment firms are 0.2% lower than prices of single-establishment firms.

to help workers transition across sectors or locations following shocks, something I show holds true in the data. To quantify the importance of multi-establishment firms in potentially mitigating the impact of negative shocks, I study a counterfactual scenario comparing an economy with multi-establishment firms to an economy without multi-establishment firms. I introduce a series of local negative shocks in both the economies and compare the impact of shocks on two objects: (i) worker reallocation and (ii) aggregate output.

I find that the existence of multi-establishment firms mitigates the impact of negative shocks on aggregate output by reallocating workers out of shocked locations, as well as limiting flows into non-employment. However, the extent of mitigation depends on the nature of the shocks. Multi-establishment firms are more valuable in mitigating the impact of shocks when the shocks are limited in geographic scope (affecting only specific regions). This is because when shocks have a wider scope, workers have a lower incentive to move to other locations or sectors of their firm, as a larger number of their firms' establishments are negatively affected at the same time. I find that without multi-establishment firms, the short-run impact of a 20% negative productivity shock on aggregate output would be 4.8% worse when the shock affects a single mesoregion of Brazil, but only 2.6% worse when the shock affects whole of the South-East region. In addition, sensitivity tests suggest that the extent of mitigation increases with the size of the shock.[5] Thus, while the multi-establishment economy exhibits lower pass-through of local shocks to the aggregate economy, the extent of mitigation depends on both the scope and the size of the local shocks.

Related literature This paper contributes to four strands of the literature. The first strand studies the implications of "superstar" firms for worker welfare. The rise of large firms has been linked with rising wage markdowns [Yeh et al., 2022, Mertens and Mottironi, 2023], increase in wage inequality [Kleinman, 2022] and the decline in labor's share of GDP [Autor et al., 2020]. At the same time, recent work emphasizes that large firms can also insure their workers against idiosyncratic shocks [Guiso et al., 2005] and provide growth opportunities via the internal labor market [Cestone et al., 2024, Carballo et al., 2024]. I build on this view by highlighting that a large share of aggregate reallocation of workers across space and sectors happens within firms. Using my model, I quantify the trade-off whereby multi-establishment firms raise workers' option value by lowering mobility frictions, but simultaneously extract larger wage markdowns through their exercise of labor-market power.

The second strand is the impact of economic shocks on workers. Recent literature has studied the impact on worker outcomes of negative shocks, such as rising import competition [Autor

[5] When the size of the mesoregion shock is 10% or 30%, the short-run impact on aggregate output in an economy without multi-establishment firms would be 3.2% and 6.7% worse, respectively, than in an economy with multi-establishment firms. Similarly, when the shock affecting the South-East region is 10% or 30%, the short-run impact in an economy without multi-establishment firms would be 2.1% and 3.3% worse, respectively, than in an economy with multi-establishment firms.

et al., 2013, Dix-Carneiro and Kovak, 2017], mass layoffs [Schmieder et al., 2023, Davis and Von Wachter, 2011, Couch and Placzek, 2010], and positive shocks such as commodity booms [Aragón and Rud, 2013, Costa et al., 2016, Benguria et al., 2024]. In this paper, I study the impact of both negative and positive shocks on worker outcomes, but contribute to the literature by highlighting the differential effect on comparable workers of multi and single-establishment firms.

The third strand I contribute to is the literature on dynamic economic geography models with forward looking households, pioneered by Artuç et al. [2010] and Caliendo et al. [2019]. The framework has been used to study the dynamic effects of infrastructure investments [Balboni, 2025], EU enlargement [Caliendo et al., 2021], and industrial policy [Caliendo and Parro, 2020]. I contribute to this framework by incorporating (i) distinction between multi and single-establishment firms and (ii) imperfect labor markets that generate endogenous markdowns. My framework can also be extended to study the impact of various policy interventions on labor market power in a dynamic setting.

The final strand of the literature examines how adjustments that occur within firms shape aggregate outcomes. This includes work studying the role of firms in driving structural change [Ding et al., 2022b], propagating economic shocks [Giroud and Mueller, 2019] and reducing trade costs [Conconi et al., 2024]. I contribute to this literature by showing that within firm reallocation accounts for a substantial share of aggregate transition of workers across locations and industries. Using the model, I also show that internal reallocation within multi-establishment firms shapes the impact of regional or sectoral shocks on the aggregate economy.

Outline of the paper The rest of the paper is organized as follows. Section 2.2 describes the data. Section 1.3 presents the empirical facts. Section 1.4 develops the model. Section 1.5 describes calibration and equilibrium. Section 1.6 presents counterfactuals. Section 1.7 concludes the paper.

1.2 Data

The main dataset used in this paper is the Brazilian *Relação Anual de Informações Sociais* (henceforth RAIS) dataset. RAIS is a matched employer–employee dataset assembled by the Brazilian Ministry of Labor since 1976 and covers the universe of formal-sector workers in the country. By law, all formally registered firms are required to report information each year on every worker employed by the firm, with large penalties for late, incomplete, or inaccurate reporting. Additionally, given that the main purpose of RAIS is to administer a federal wage bonus at the end of the year, firms have incentives for truthful reporting. Dix-Carneiro and Kovak [2017] provide further details on the background and construction of the RAIS dataset.

The data contain a worker identifier (PIS), which remains with the worker throughout their life-

time and allows me to track individual workers over time. Additionally, each job spell of a worker is associated with an establishment, and each establishment is identified by a 14-digit registration number (CNPJ) that does not change over time. The first eight digits of the CNPJ identify the firm to which the establishment belongs. On the worker side, the data contain information on age, gender, education, tenure at the establishment, occupation, and wages.[6]

For each establishment, the dataset contains information on its geographic location and industry. The definition of a location is a "microregion" of Brazil, which groups together municipalities with similar geographic and productive characteristics and follows the notion of a local labor market [Dix-Carneiro and Kovak, 2017]. I follow the 2010 boundaries of microregions, resulting in 557 microregions. The definition of an industry is the five-digit CNAE classification code (there are 564 five-digit CNAE codes). Each establishment and firm in the RAIS dataset is assigned a CNAE code based on its primary activity.

With information on both the location and industry of the establishment, I can observe workers migrating across locations or changing industries between years. Importantly, because I observe both the establishment and the firm of the worker, I can track whether such transitions occur within the firm.[7]

Throughout this paper, I focus on workers who were employed in December of each calendar year and exclude workers employed in government and quasi-government sectors. Appendix Tables A.1 and A.2 present summary statistics at the firm and worker levels, respectively, for the year 2005. The average firm employed 18 workers in 2005, 4.14% of firms were multi-establishment, and 1.75% of firms were multi-location (i.e., operated in more than one microregion). Roughly 41% of workers were employed by a multi-establishment firm and 33% by a multi-location firm, where a location corresponds to a microregion of Brazil.[8]

To complement the RAIS dataset, I use export transaction data from the *Secretaria de Comércio Exterior* (henceforth SECEX). Between 1997 and 2001, the data contain information on the value of exports at the product–establishment–year level. From 2002 to 2009, the data contain a binary indicator at the product–firm–year level for whether the firm exported a given product in that year. I link the SECEX data to RAIS using a common establishment or firm identifier.

[6]Wages in RAIS include wages, salaries, and any bonuses paid before taxes.

[7]The U.S. counterpart to the RAIS dataset would be the LEHD dataset. However, a data limitation makes LEHD less suitable for studying within-firm, across-establishment transitions. As noted by Carballo et al. [2024], establishment-to-establishment transitions within firms are not perfectly observed in LEHD because firms often group multiple establishments within a state under a single SEIN identifier. In addition, each state must provide separate approval to use LEHD for a given project, limiting the geographic scope of the data. In contrast, RAIS covers the entirety of Brazil and uniquely identifies each establishment.

[8]Figure A.2 shows the share of employment in multi-establishment and multi-location firms across Brazilian microregions in 2005.

1.3 Empirical facts

Multi-establishment firms are an important feature of modern economies: they accounted for 41% of total formal employment in Brazil and roughly half of total wages paid in 2005. This phenomenon is not Brazil specific. Multi-establishment firms accounted for 57% of employment in the US [Carballo et al., 2024] in 2005 and 34% of employment in Germany in 2012 [Gumpert et al., 2022]. In this section, I document four facts on multi-establishment firms and worker mobility within those firms.

1.3.1 Fact 1: Multi-establishment firms are multi-location and multi-sector

Using the RAIS dataset, I first show that multi-establishment firms are not just multi-establishment: they are both multi-location, thus operating in multiple locations, and multi-industry, with their operations spanning multiple industries.

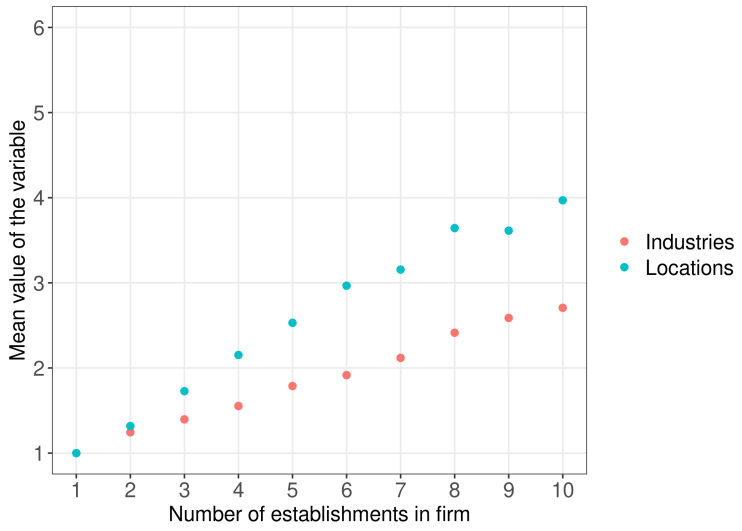
Figure 1.1 plots the average number of locations and industries based on the number of establishments in the firm for the year 2005. As the figure shows, multi-establishment firms do not operate in single locations or industries: the average firm with 10 establishments operates in 4 locations and 3 industries, with both the average number of locations and industries increasing linearly with the number of firm establishments. Figure A.3 in the appendix shows the average number of locations and industries by number of firm establishments for manufacturing and service firms separately. For a given number of firm establishments, manufacturing firms tend to have a higher number of average locations and industries relative to service firms, with the average manufacturing firm with 10 establishments operating in 6 locations and 3 industries.

The number of unique industries within the firm could be underreported if firm respondents report the same industry for the establishment as the firm, even if the activity of the establishment may be very different. To further demonstrate the fact that the activities of establishments can vary substantially within the firm, I use establishment-level export data from 2001. The SECEX data records the value of exports at the level of product-establishment-year, where each product is defined at the HS6 digit level.

Appendix figure A.4 evaluates the extent of overlap in the products exported by different establishments within the same firm. For each firm, I define two measures: (i) share of products the firm exported that are exported by all establishments and (ii) share of products the firm exported that are exported by only one establishment. Panel (a) of figure A.4 shows that the average share of products exported by all establishments of the firm declines with the number of establishments of the firm that export. In other words, few products are exported from all of the firm's establishments. The corollary of figure A.4 panel (a) is panel (b), which shows the average share of products which are exported by only one establishment within the firm. For firms with 4 exporting establishments,

the average share of products exported by only one establishment is 70%, suggesting substantial differentiation in the product mix of each establishment within the firm. This highlights how, at least for manufacturing exporters, substantial heterogeneity exists in terms of what is produced in different establishments of the same firm.

Figure 1.1: Average locations and industries by number of firm establishments (2005)



1.3.2 Fact 2: Within firm reallocation is a large share of aggregate worker reallocation

The RAIS dataset allows me to follow workers over time, and identify their transitions across locations and industries. Importantly, given that RAIS has information on both the establishment and the firm of the worker, I can track the extent to which those transitions occur within the firm.

Table 1.1 shows transition of workers across firms and locations between 2004 and 2005. The sample is restricted to workers who were part of formal employment at the end of both calendar years. As the table shows, roughly 16% of the workers changed their firm and 6% of the workers changed their location, moving to a different microregion. However, 25% of that migration happened while the worker stayed within the same firm. There is a systematic component to such migration: the unconditional probability of workers migrating and ending in the same firm is less than 0.01%.

Note that table 1.1 represents all workers, not just those who work in multi-establishment firms. Table A.3 in the appendix shows the corresponding transition matrix for workers who were working in a multi-establishment firm in 2004. A higher share of multi-establishment firm workers migrate relative to all workers, and conditional on migrating, 37% of such workers end up in the same firm. Appendix tables A.4 and A.5 further distinguish the migration patterns of low and

Table 1.1: Worker transition across firms and locations (2004-05)

	Same location	Different location
Different firm	11.3%	4.6%
Same firm	82.7%	1.5%

high-skilled workers respectively, using the classification of occupations into high and low skilled used in Helpman et al. [2016]. Conditional on migrating, high-skilled workers are more likely to stay within the same firm, relative to low-skilled workers. The fact that a large share of migration across locations is within the firm continues to hold even at higher levels of geographic aggregation. Appendix Tables A.7 and A.8 show the transition matrix at firm-mesoregion and firm-state level respectively. Compared to 557 microregions, Brazil has 137 mesoregions and 27 states (including the Federal district of Brasília). Roughly 23% of migration across mesoregions, and 18% of migration across states happens while the worker stays within the same firm.[9] Appendix Figure A.5 panel (a) shows the share of workers in each state linked with other states through their firm.

A similar analysis can be conducted for worker transition across industries, where industries are defined based on the 5-digit CNAE code of the establishment. Table 1.2 shows the transition of workers employed in both 2004 and 2005 across firms and industries. 83.6% of workers stayed in the same industry across both years, while 16.4% of the workers switched industries. However, roughly 27% of workers who changed industry between 2004 and 2005 did so while staying within the same firm.

Table 1.2: Worker transition across firms and industries (2004-05)

	Same industry	Different industry
Different firm	3.8%	12%
Same firm	79.8%	4.4%

While table 1.2 focuses on industries, the same analysis can be done at a broader level of aggregation. Using classifications provided by Brazilian statistical agency IBGE, I classify the 5-digit CNAE codes into one of the following three sectors: commodity, manufacturing, or services. Appendix table A.9 reports worker transitions across firms and sectors. Unsurprisingly, only 4.2% of workers changed sectors, which is much lower than the 16.4% that changed industries. However,

[9]Carballo et al. [2024] estimate that 27% of between-state transitions occur within the same firm in the US. A large share for the US is unsurprising as the US has a much larger share of total employment in multi-establishment firms relative to Brazil: 57% of employment in US vs 41% of formal employment in Brazil in 2005.

19% of workers who changed sectors did so while staying within the same firm, highlighting the important role of firms in enabling worker transitions across sectors. Appendix Figure A.5 panel (b) shows the share of workers in each sector linked with other sectors through their firm.

1.3.3 Fact 3: Multi-establishment firms mitigate the impact of negative shocks on their workers

Section 1.3.2 shows that the within-firm channel is an important one through which workers transition across locations and industries. This subsection will tackle the following question: Do multi-establishment firms mitigate the impact of negative shocks on their workers through internal reallocation? The ideal experiment involves comparing two identical workers who are hit with the same negative shock, but one of them works for a multi-establishment firm while the other does not. This section aims to implement this experiment and test whether the worker belonging to the multi-establishment firm is able to deal better with the shock by exploiting opportunities in other establishments of the same firm.

1.3.3.1 Event study framework

The shock I use the closure of a worker's establishment as the negative shock to the worker.[10] A number of papers have studied the impact of job displacement arising from establishment or firm closure on worker outcomes (see for example, Couch and Placzek [2010] and Wachter et al. [2011]). An attractive feature of using establishment or firm closures is that job losses arising from such closures involve exogenous and involuntary separations, as opposed to being an endogenous decision by the worker [Jacobson et al., 1993]. The focus of this section will be to identify differential responses to establishment closures of otherwise similar workers, with the workers differentiated based on whether they belong to multi or single-establishment firms before closure.[11]

Appendix table A.12 shows that when an establishment of a multi-establishment firm closes, it is associated with a firm closing only 9% of the time, suggesting that most workers affected by such closures potentially have the opportunity to transfer to other establishments of the firm. By contrast, closure of an establishment belonging to a single-establishment firm is associated with firm closure 99% of the time, suggesting that these workers will have no possibility to stay within

[10] While this section focuses on establishment closures, appendix table A.10 shows that within firm reallocation of workers is an important channel for staffing new establishments opened by firms. When an existing firm opens a new establishment, 22.3% of hiring in that establishment comes from within the firm.

[11] Other papers in the literature have studied differential worker response to job losses along alternative margins. Schmieder et al. [2023] show that job displacements are particularly costly during recessions and Moretti and Yi [2024] show that worker responses to firm closures differ based on whether they belong to larger, thicker labor markets or not.

the same firm. Using establishment closures is useful in this context because multi and single-establishment firm workers face the same shock: their job spell ends and they cannot continue with the same establishment, facing displacement.

Sample selection I use a 20% sample of workers working in 1998 and track them between 1998 and 2011. I restrict the sample by keeping workers who were male and between the ages of 24 and 50 in 1998, and show up in RAIS at least 3 times between 1998 and 2011. The RAIS dataset allows me to identify establishment closures based on the establishment identifier ceasing to exist. I restrict establishment closures to establishments that operated for at least 3 years before closing. In the restricted sample, roughly 15% of the workers would go on to experience an establishment closure.

Identification Directly comparing multi and single-establishment firm workers who face an establishment closure may violate the parallel trends assumption of the DiD estimator, as characteristics of these two groups of workers could differ substantially at the baseline (see the first two columns of appendix table A.13). To avoid this problem, I use a triple difference specification to account for differential pre-trends between multi and single-establishment workers, by utilizing workers who did not face an establishment closure. The triple difference regression exploits variation along the following three margins: (i) multi vs single-establishment (ii) affected vs unaffected by closure and (iii) pre vs post closure.

For each worker affected by establishment closure (treated), I select one unaffected worker (untreated) using a two-step matching procedure. The first step matches within the year before closure and firm type (multi or single-establishment).[12] In the second step, the best match is identified based on variables such as wage in $t = 0$, wage in $t - 1$, tenure in the t=0 establishment, labor force participation in $t - 1$, age and education level. Appendix table A.13 provides the summary statistics of untreated and treated workers, differentiating them based on whether they belonged to multi or single-establishment firm at $t = 0$. Matching is done without replacement.

The exact specification used for the event study is as follows:

$$\begin{aligned} y_{it} = & \sum_{o=-4}^{o=6} \alpha_o (T_i \times \mathbf{1}[\text{time=o}]) + \sum_{o=-4}^{o=6} \phi_o (M_i \times \mathbf{1}[\text{time=o}]) \\ & + \sum_{o=-4}^{o=6} \beta_o (T_i \times M_i \times \mathbf{1}[\text{time=o}]) + \delta_o + \lambda_i + \gamma_{mt} + \epsilon_{it}, \end{aligned} \tag{1.1}$$

In equation 1.1, y_{it} represents the outcome for worker i at time t. $T_i$is a binary variable that equals 1 if the worker was affected by an establishment closure, while M_i is a binary variable that equals 1 if the worker worked for a multi-establishment firm in year $t = 0$. I include worker

[12] I refer to $t = 0$ as the year before closure, which is the last year of operation for the establishment.

fixed effects λ_i and control for location-year specific shocks via microregion-year fixed effects γ_{mt}. β_o are the coefficients of the triple difference term of interest, and represent the differential treatment effect of establishment closure for multi vs single-establishment workers o years from closure. The key identifying assumption is parallel trends: the difference in outcomes of multi and single-establishment treated workers would trend similarly to the difference in multi and single-establishment untreated workers in the absence of establishment closure [Olden and Møen, 2022]. For all specifications, I cluster standard errors at the level of microregion.

1.3.3.2 Impact of establishment closure on migration and labor force participation

I use the above triple difference specification to study the differential impact of establishment closure on multi vs single-establishment firm workers. For migration, I define $y_{it} = 1$ if the location of the worker in year t is different from their location in $t-1$, and 0 otherwise.[13] For dropping from formal labor force, I define $y_{it} = 1$ if the worker is not in the RAIS dataset, and thus not in the formal labor force, and 0 otherwise.[14]

Panel (a) of figure 1.2 plots the β_o coefficients from equation 1.1 for 4 years before and until 6 years after the establishment closure, setting $o = -1$ as the reference period. The estimates suggest that in the period following the last year of operation of the establishment, workers of multi-establishment firms are 15 percentage points less likely to drop from the labor force relative to workers of single-establishment firms. The difference in their labor force participation narrows over time, but does not completely go away: even 6 years after the closure of the establishment, multi-establishment firm workers are 5 percentage points less likely to be out of the formal labor force relative to their single-establishment counterparts.[15]

Panel (b) of figure 1.2 plots the coefficient β_o from equation 1.1 for migration as the dependent variable.[16] The figure suggests that multi-establishment firm workers are 3.7 percentage points more likely to migrate in the period after establishment closure than single-establishment firm workers. Given that roughly 6 percent of the workers migrate every year, this represents a 60% increase in the probability of migrating over the baseline rate. Appendix figure A.7 plots the treat-

[13] If the worker is not in the labor force in period t, I will not have information on their location, and assign their previous known location as the location for period t.

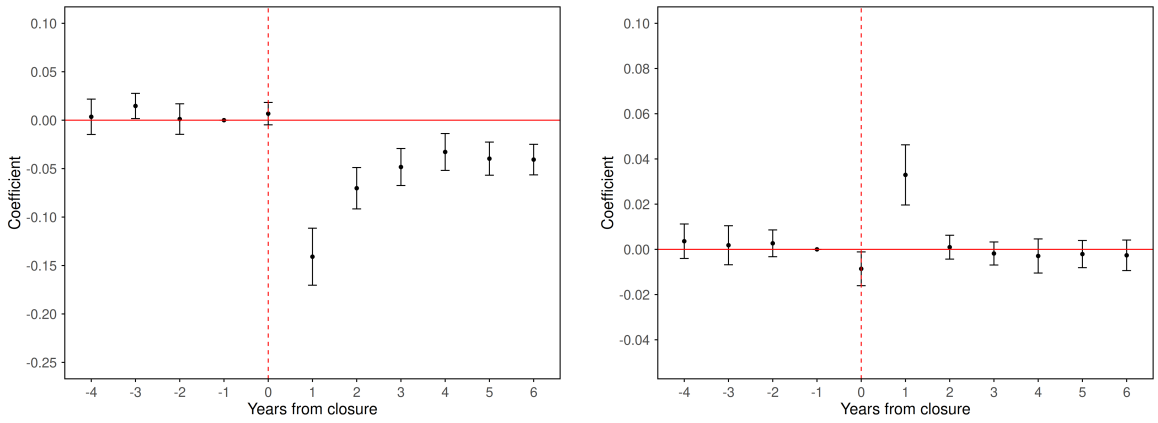
[14] Figure A.8 in the appendix plots the coefficients of equation 1.1 with Inverse Hyperbolic sine as the dependent variable. Figure A.9 in the appendix show the evolution of average wages relative to $t = 0$ for treated and untreated workers by multi-establishment status.

[15] While panel (a) of figure 1.2 plots the coefficients from triple difference estimator, it is instructive to look at the treatment effect of establishment closure by multi-establishment status. Figure A.6 plots the treatment effect of a difference-in-difference estimator, but separately for multi vs single-establishment firm workers. The triple difference estimator of equation 1.1 is equivalent to the difference between the two DiD estimators presented in figure A.6 [Olden and Møen, 2022].

[16] The location of a worker is unknown when the worker is not in the formal labor force, and thus not in the RAIS dataset. In such a case, I assign the last known location of the worker as the current location.

ment effect of establishment closure using a DiD specification separately for multi-establishment and single-establishment firm workers. Figure A.7 suggests that migration is fairly responsive to establishment closures, with migration rates even for treated single location firm workers being higher than untreated single-establishment workers following establishment closures. This worker level response stands in contrast to the labor market level findings in Autor et al. [2013] and Dix-Carneiro and Kovak [2017], who both rule out interregional migration as a response to negative trade shocks.

Figure 1.2: Worker level response to establishment closures



(a) Dep. variable: $\mathbf{1}[\text{Not in formal LF}]_{it}$ (b) Dep. variable: $\mathbf{1}[\text{Migrated}]_{it}$

Note: These figures plot estimates of β_o from the DDD estimator in equation (1) for $o \in [-4, 6]$ (with $o = -1$ omitted). The binary dependent variable in panel (a) is 1 if worker is not in the formal labor force. The binary dependent variable is panel (b) is 1 if the location of the worker is different in current period relative to previous period. Error bars show 95% confidence intervals from clustering at the microregion of the worker prior to establishment closure.

1.3.3.3 Within firm reallocation in response to establishment closure

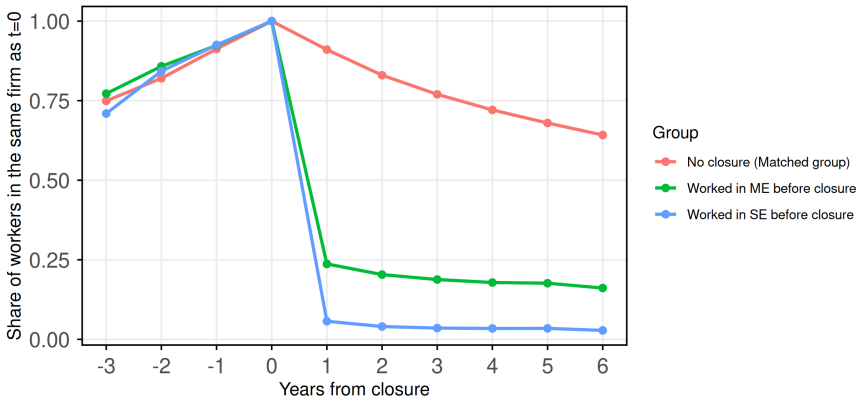
To what extent is the differential response of multi and single-establishment firm workers presented in figure 1.2 driven by the potential for multi-establishment firm workers to reallocate within the same firm following establishment closure? Figure 1.3 provides some evidence. Figure 1.3 plots the share of workers that continue working for the same firm as $t = 0$ for three groups of workers: multi-establishment firm workers who faced establishment closures, single-establishment firm workers who faced establishment closures and the matched group of workers who did not face establishment closures.

Roughly 25% of multi-establishment firm workers continued working in the same firm following the closure of their establishment, compared to 4% of single-establishment firm workers.[17]

[17]The share of single establishment workers continuing in the same firm after closure is not 0 as it is possible for a single establishment firm to close one establishment and open another establishment while keeping the same firm identifier.

This shows that multi-establishment workers were to a large extent able to exploit opportunities and transfer to other establishments in their firm, an option that was largely unavailable to their single-establishment counterparts.

Figure 1.3: Continuing with the same firm after establishment closure



1.3.3.4 Robustness

A potential concern with the shock described in section 1.3.3.1 is that single and multi-establishment firm workers facing establishment closures are not experiencing the same shock. The multi-establishment firm closing an establishment could be restructuring operations within a microregion, for example, by transferring employees from one establishment to another in the same location. In such a scenario, the nature of the shock is very different for single and multi-establishment workers.

As a robustness check, I redefine the shock from establishment to location closures. Location closure implies that the firm closes all of its establishments within a given location. Workers affected by such shocks no longer have the opportunity to transfer to another establishment of the firm in the same location. To stay within the firm, they will have to migrate out of their microregion. I again use the triple difference specification of equation 1.1, but redefine T_i and M_i.[18] The differential response is similar to the results in figure 1.2. Figure A.13 in the appendix shows that workers of multi-location firms are 17 percentage points less likely to drop from the labor force, and 6 percentage points more likely to migrate, relative to workers of single-location firms following closure of all establishments of their firm in their location.[19]

[18] $T_i = 1$ if the worker was affected by a location closure, while $M_i = 1$ if worker worked for a multi-location firm in year $t = 0$. The triple difference specification now tests whether workers of multi-location firms respond differentially than workers of single-location firms following the closure of all establishments of their firm in their location.

[19] Again, the ability to relocate to other establishments of the firm, this time to establishments in other locations,

As an alternative to exploiting establishment closures as worker level shocks, I examine whether multi-establishment firms help workers cope with adverse shocks by focusing on trade shocks, such as rising competition from Chinese imports (see Autor et al. [2013]), or exogenous tariff reductions, as in Dix-Carneiro [2014]. The underlying idea is that multi-establishment firms operate across multiple industries and, when faced with industry-specific import competition, may be able to mitigate the impact on workers by reallocating them internally to unaffected or growing sectors. As a result, workers in exposed sectors may fare better when employed by multi-establishment firms compared to their counterparts in single-establishment firms.

To study such a shock, I exploit the expiration of the Multi-Fiber agreement in 2005, which lifted export quotas on specific textile and clothing products from China to developed countries, such as the US, Canada, and the EU. Section A.2 in the appendix describes the background, construction of the shock, and the results. In summary, the results suggest that multi-establishment firm workers indeed were less likely to be affected by import competition from China. However, this happened not because they transitioned to other establishments of their firm, but because their establishments were less likely to close from the competition in the first place. The protection afforded to multi-establishment firm workers from negative shocks that comes from them being in a more productive firm is interesting, but not the focus of this paper.[20] This also highlights the attractiveness of the shock exploited in Section 1.3.3.2: both multi and single-establishment workers are affected by closure of their establishment, and face displacement.

1.3.4 Fact 4: Multi-establishment firms allow workers to exploit positive shocks

This section explores whether working for a multi-establishment firm allows workers to exploit positive shocks. Multi-establishment firms could respond to local productivity booms or place-based incentives in locations they operate in by reallocating workers internally.[21] Giroud and Mueller [2015] use opening of new airline routes to show that firms respond to positive shocks in a location of an establishment by reallocating capital and labor to that establishment. Similarly, if firms operate in a sector that experiences a positive shock, they could respond by internally reallocating resources towards the sector.

I study this channel by examining the response of Brazilian firms to the commodity price boom

explains an important part of the differential response: appendix figure A.14 plots the share of workers that continue working for the same firm following location closure. Multi-location firm workers are more likely to stay with the same firm relative to single location firm workers following location closures.

[20] This point aligns with Melitz [2003], which highlights how least productive firms in a sector exit while most productive firms expand following exposure to international trade.

[21] Note that firms could also respond to such productivity changes or regional incentives even if they do not already have establishments in a given location, by opening new establishments.

in the 2000s. Based on a global price index, Benguria et al. [2024] show that commodity prices increased by 40% between 2002 and 2007, and by 60% between 2002 and 2011. The boom was thus a positive sector specific shock. To what extent did working in a firm that had operations in the commodity sector allow workers to move to that sector?

Analyzing worker reallocation across sectors, I find that among the workers employed in the commodity sector[22] in 2007, 27% had come from non-commodity sectors, based on their sectoral affiliation in 2002. Importantly, 15% of those who had moved from a non-commodity to commodity sector were in the same firm in 2002 and 2007. Note that this is a lower bound on how many workers transitioned to the commodity sector within the firm. A worker could have transferred to the commodity sector within the firm, and then moved to another firm while staying in the commodity sector.

I formally test whether the opportunities to transition to the commodity sector within the firm made workers more likely to move and work in the sector. I compare otherwise similar workers working in a non-commodity sector in 2002 who differ based on having a commodity establishment in their firm. For example, consider two tailors in textile establishments A and B in Rio de Janeiro in 2002, where establishment A belongs to a firm that also operates a commodity establishment. Was the tailor in establishment A more likely to move to the commodity sector by 2007 compared to the tailor in establishment B?

Table 1.3: Transition likelihood from non-commodity to commodity sector

Dependent Variable:	$\mathbf{1}[\text{Commodity sector}]_{2007}$		
	All	Manufacturing in 2002	Services in 2002
	(1)	(2)	(3)
$\mathbf{1}[\text{Commodity plant in firm}]_{2002}$	0.055***	0.019*	0.061***
	(0.011)	(0.010)	(0.012)
Worker and Firm controls	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes
Origin Industry-Origin location FE	Yes	Yes	Yes
Observations	3,485,476	569,200	2,916,264
Mean dep. variable	0.022	0.035	0.020

Note: Sample is 20% of workers working in a non-commodity sector in 2002 who were still formally employed in 2007. Worker controls include worker wage and tenure at establishment. Firm control includes firm size. Standard errors clustered at the microregion level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

[22]Using classifications provided by Brazilian statistical agency IBGE, I classify the 5-digit CNAE codes into one of the following three sectors: commodity, manufacturing, and services. Commodity includes agriculture, mining, and forestry.

Column 1 of table 1.3 shows that non-commodity workers were 5.5 p.p. more likely to transition to the commodity sector if they started in a firm that had a commodity plant.[23] To ensure that the comparison is across otherwise similar workers, I include occupation fixed effects, origin industry $\times$ origin microregion fixed effects, and control for worker wages, tenure and firm size. The size of the coefficient is large relative to the average share of workers who transitioned from non-commodity to commodity sector between 2002 and 2007, which was 2.2%. The coefficient in column 1 of table 1.3 is driven by moves within and outside the firm. However, decomposing the coefficient, I find that at least 84% of the coefficient is driven by moves within the firm.[24] Column 2 and 3 of table 1.3 compare workers who started in manufacturing and service sectors respectively.

What about potential wage gains? Table A.16 in the appendix shows that while having a commodity establishment in the firm per se in 2002 did not lead to higher wages in 2007, those who moved to the commodity sector did experience wage gains of 10.4%. In addition, table A.17 shows the extent to which moving to the commodity sector was accompanied by migrating to a different microregion. Workers who had a commodity plant in their firm in 2002 and had moved to the commodity sector by 2007 were 4.2 p.p. more likely to have migrated, relative to comparable workers who did not have a commodity plant in their firm. This means that the sectoral reallocation within the firm owing to the commodity boom also had an important spatial component.

1.4 Model with multi-establishment firms and endogenous markdowns

Guided by the four facts presented in section 1.3, I now proceed to build a model that allows me to study the impact of within-firm worker mobility on labor reallocation, monopsony power and worker welfare. I build on the dynamic economic geography model in Caliendo et al. [2019] that incorporates forward looking agents who face mobility frictions across locations and sectors. Given the empirical facts outlined in section 1.3, I extend the model in Caliendo et al. [2019] by (i) incorporating the distinction between single and multi-establishment firms, (ii) introducing differing mobility frictions within and across firms, and (iii) having imperfectly competitive labor markets. The last extension allows the firm to potentially extract differential wage markdowns depending on the "amenity" of access to opportunities within the firm in the future, and explain part of the markdown difference between multi and single-establishment firms in the literature (see

[23] Table A.18 in the appendix shows the impact on the intensive margin: how the likelihood of transitioning to commodity sector increases as the share of employment in the commodity sector of the firm goes up.

[24] Among workers who stayed in the same firm between 2002 and 2007, the effect is 0.046, whereas among movers across firms the effect is 0.009. Thus, the majority of the baseline association (roughly 84% of the magnitude) is concentrated among within-firm movers.

Yeh et al. [2022]).[25]

1.4.1 Setup

The economy consists of a discrete number of locations indexed by $n \in 1, ..., N$ and a discrete number of sectors $s \in 1, ..., S$. Each location-sector combination has a number of establishments denoted by e. The location of each establishment and their distribution across locations and sectors is fixed. However, the employment in each establishment is determined in equilibrium. Establishments can differ not just in terms of their location or sector, but also based on the other establishments within their firm. Each establishment produces output of only a single sector. Time is discrete and indexed by $t = 1, ..., T$.

1.4.2 Workers

Workers in this model are homogeneous. Each period, the worker may be either employed or non-employed. If employed, the worker is endowed with a unit of labor which they supply inelastically to the establishment they belong to, and earn the wage offered by the establishment. Given the wage, they allocate consumption over goods from all sectors based on preferences given by a Cobb-Douglas aggregator $U(C_t^e) = \Pi_{s=1}^{S}(c_t^{e,s})^{\alpha_s}$. If the worker is non-employed, they obtain consumption in terms of home production b_n.

At the end of each period, they may relocate to another establishment in the economy, subject to mobility frictions, wage offers and their idiosyncratic preference shock across establishments, which are independent and identically distributed across workers, establishment and time. The lifetime utility of a worker currently working for establishment e in location n at time t is given by the following

$$v_t^e = U(C_t^e) + \max_{e'} \left\{ \beta E[v_{t+1}^{e'}] - \gamma_{ee'} + \epsilon_t^{e'} \right\}$$

$$\text{where} \quad C_t^e = \begin{cases} b_n, & \text{if the worker is not employed,} \\ w_t^e / P_t^n, & \text{otherwise.} \end{cases}$$

$\gamma_{ee'}$ captures the mobility cost between origin establishment e and destination establishment e', is time-invariant, and measured in terms of utility. w_t^e is wage offered by establishment e at time

[25] I do not have the necessary data to calculate establishment specific markdowns and then show that markdowns for multi-establishment firms are lower than single-establishment firms. However, I do a comparable exercise with worker level wage data. Appendix table A.19 shows the impact of growth of firm size and number of firm establishment on worker wages using an AKM regression that accounts for firm and worker fixed effects. I find that while growth in firm size leads to increase in worker level wages, growth in the number of firm establishments leads to a decline in worker wages. On average, an increase of 100 establishments of a firm results in 2% lower wages.

t and P_t^n (defined later) is the ideal price index in location n where the establishment is located. Workers discount the future with the discount factor β . $\epsilon_t^{e'}$ captures the worker's idiosyncratic preference draw for establishment e'. I assume that $\epsilon_t^{e'}$ is iid Gumbel distributed following Artuç et al. [2010] with parameters $(-\gamma\nu, \nu)$, where γ is the Euler constant.[26] $\nu > 0$ captures the variance of the shocks across establishments: a higher value of ν implies higher variance of shocks across establishments.[27] With this assumption, following Caliendo et al. [2019] and Balboni [2025], the expected lifetime utility of a worker working in establishment e at time t, $V_t^e \equiv E[v_t^e]$, can be expressed as:

$$V_t^e = U(C_t^e) + \nu \log\Big(\sum_{e'} \exp(\beta V_{t+1}^{e'} - \gamma_{ee'})^{1/\nu}\Big) \tag{1.2}$$

The Gumbel assumption also yields an equation that captures the share of workers that start in establishment e in period t and migrate to establishment e'.

$$\mu_t^{e\to e'} = \frac{\exp(\beta V_{t+1}^{e'} - \gamma_{ee'})^{1/\nu}}{\sum_{e'} \exp(\beta V_{t+1}^{e'} - \gamma_{ee'})^{1/\nu}} \tag{1.3}$$

As equation 1.3 shows, ceteris paribus, a higher expected lifetime utility attracts more workers to an establishment, while higher mobility costs to that establishment deter them, with a migration elasticity of $1/\nu$. Finally, the evolution of labor in each establishment is given by the distribution of workers across establishments in the previous period and the corresponding migration shares.

$$L_{t+1}^{e'} = \sum_e \mu_t^{e\to e'} L_t^e \tag{1.4}$$

1.4.3 Production and price indices

Each establishment specializes in producing its own unique variety in a sector. Production is linear in labor and given by the function $q_t^e = A_t^{ns} L_t^e$, where L_t^e is labor employed by the establishment and A_t^{ns} is the productivity of the establishment based on the location n and sector s of the establishment. Thus, all establishments within a location-sector have the same productivity.

Within a sector, consumers have CES preferences across varieties produced by different establishments, with an elasticity of substitution η . Given this, total demand for output of an establishment is the sum total of quantity demanded in each location, and given by the following:

$$q_t^e = \sum_m \frac{(p_t^e \tau_{n(e)m})^{-\eta}}{(P_t^{ms})^{1-\eta}} \kappa_s Y_t^m \tag{1.5}$$

[26] More specifically, the CDF of this distribution is given by $F(\epsilon) = \exp\Big(-\exp\Big(-\frac{\epsilon}{\nu} - \gamma\Big)\Big)$

[27] The variance of the distribution is $\frac{\pi^2\nu^2}{6}$.

p_t^e in equation 1.5 is the price at origin of the output produced by establishment e. $\tau_{n(e)m}$ is the iceberg trade cost of shipping the good from the origin location of the establishment to the destination location. Y_t^m captures total income of those who live and work in location m. P_t^{ms} is the price index for sector s in location m and aggregates the prices of all establishments that belong to sector s. Aggregating over local sectoral price indices gives the aggregate price index in location m

$$\begin{aligned} P_t^m &= \prod_s \left(P_t^{ms}/\kappa_s\right)^{\kappa_s} \\ \text{where} \quad \left(P_t^{ms}\right)^{1-\eta} &= \sum_{e \in s} \left(p_t^e \tau_{n(e)m}\right)^{1-\eta} \end{aligned} \tag{1.6}$$

1.4.4 Labor demand: Bertrand competition

I now outline the profit maximization problem of producers. In section 1.4.4.1, I start with the case where each establishment acts independently. I assume that labor markets are characterized by imperfect competition. Specifically, establishments compete à la Bertrand, choosing their wage while taking as given the wage of other establishments. I then outline in section 1.4.4.2 the case where some establishments belong to the same firm, and profit maximization operates at the level of the firm. Note that while workers are forward looking and solve a dynamic optimization problem, establishments (and later firms) solve a static profit maximization problem.

1.4.4.1 Establishment profit maximization

$$\begin{aligned} \max \quad & p_t^e q_t^e - w_t^e L_t^e \\ \text{subject to} \quad & q_t^e = \sum_m \frac{\left(p_t^e \tau_{n(e)m}\right)^{-\eta}}{\left(P_t^{ms}\right)^{1-\eta}} \kappa_s Y_t^m \quad \text{(CES demand)} \\ & q_t^e = A_t^{ns} L_t^e \quad \text{(Production function)} \\ & L_t^e = \left(\frac{w_t^e}{P_t^e}\right)^{\beta/\nu} \left(\Theta_{t+1}^e\right)^{\beta} \left(\sum_{e'} \frac{\exp(-\gamma_{e'e})^{1/\nu}}{\Theta_t^{e'}} L_{t-1}^{e'}\right) \quad \text{(Labor supply)} \end{aligned} \tag{1.7}$$

The labor supply equation in equation 1.7 is an alternative representation of equation 1.2, with the derivation shown in appendix A.1.1. The term Θ_{t+1}^e in the labor supply equation is an aggregate index that sums across the expected lifetime utilities of different establishments in the economy, net of transition costs $\Theta_{t+1}^e = \sum_{e'} \exp(\beta V_{t+1}^{e'} - \gamma_{ee'})^{1/\nu}$.[28] The labor supply equation shows that for a given wage, the establishment can attract more workers if it has a larger Θ_{t+1}^e, or if it offers lower frictions $\gamma_{e'e}$ with respect to other establishments in the economy.

[28] Note that the object Θ_{t+1}^e is the same as the term inside the log in equation 1.2.

Following Felix [2021], I define markdown of an establishment as the ratio of Marginal Revenue Product of Labor (MRPL) and wages. Given the production function in equation 1.2, markdown turns out to be the ratio of revenue and wage bill of the establishment, i.e. $MD_t^e = \frac{p_t^e A_t^{ns}}{w_t^e} = \frac{p_t^e q_t^e}{w_t^e l_t^e}$. The maximization problem leads to the following proposition about establishment specific wage markdowns

Proposition 1: *When establishments maximize profits and compete à la Bertrand in the labor market, establishment specific markdowns are given by*

$$\begin{aligned} MD_t^e &= \frac{p_t^e q_t^e}{w_t^e l_t^e} = \frac{\frac{\eta}{\eta-1}\left[\frac{\beta+\nu}{\beta} - \Phi_t^e\right]}{1-\Phi_t^e} \\ \text{where} \quad \Phi_t^e &= \frac{\sum_{e'}\left(\mu_{t-1}^{e'\to e}\right)^2 L_{t-1}^{e'}}{\sum_{e'}\left(\mu_{t-1}^{e'\to e}\right) L_{t-1}^{e'}} \end{aligned} \tag{1.8}$$

Proof: See appendix section A.1.1.1.

The establishment specific markdown in equation 1.8 depends on elasticity of demand η, the discount factor β and the variance of worker preference shocks across establishments, captured by ν. Finally, as in Berger et al. [2022] and Felix [2021], the notion of market shares shows up in the expression for markdown in the form of Φ_t^e, which captures the monopsony power of the establishment, with $0 \leq \Phi_t^e \leq 1$. However, unlike those papers where the key statistic is the payroll share of the firm/establishment, in equation 1.8, Φ_t^e depends on the share of workers transitioning from all other establishments to establishment e between period $t-1$ and t, i.e. $\mu_{t-1}^{e'\to e}$. This share is the same as the transition shares in equation 1.3. The numerator of Φ_t^e is akin to a labor-weighted Herfindahl index.

The limiting cases of equation 1.8 include both perfect and monopsonistic competition in the labor market. First, as the variance of worker preferences across establishments $\nu \to 0$, such that worker preferences are indifferent across establishments in the economy, the markdown $MD_t^e \to \frac{\eta}{\eta-1}$, which is the markdown (or markup) obtained when labor markets are perfectly competitive and firms compete in product markets under monopolistic competition. Second, as each establishment becomes small relative to the rest of the economy, so that $\mu_{t-1}^{e'\to e} \to 0 \; \forall e'$, the markdown $MD_t^e \to \frac{\eta}{\eta-1}\frac{\beta+\nu}{\beta}$, which is the same as markdown under monopsonistic competition in the labor market.[29]

Finally, the markdown also depends on the level of mobility frictions across establishments. When mobility costs $\gamma_{ee'} \to \infty \forall e \neq e'$, workers stay in their own establishment every period, with $\Phi_t^e \to 1$ and $MD_t^e \to \infty$. On the other hand, in an economy without mobility frictions (and

[29]Under monopsonistic competition, establishments are "small" and take the aggregate index $\Theta_t^{e'}$ of equation 1.7 as given. They do not account for how their wage offer affects the aggregate index $\Theta_t^{e'}$. This is similar to the Armington assumption under monopolistic competition in product markets, where firms do not account for how their price choice affects the overall price index.

assuming all establishments offer the same value V_t^e) $MD_t^e \rightarrow \frac{\frac{\eta}{\eta-1}\left[\frac{\beta+\nu}{\beta}-\frac{1}{N}\right]}{\left[1-\frac{1}{N}\right]}$, with N representing the number of establishments in the economy.

1.4.4.2 Firm profit maximization

Having derived the markdown in the case where each establishment acts independently, I now solve the maximization problem of a firm represented by F that has multiple establishments. When multiple establishments operate within the firm, it is reasonable to think that the firm coordinates hiring decisions across its establishments so that firm level profit is maximized. The solution to the profit maximization problem of a firm with multiple establishments leads to the following proposition

Proposition 2: *When firms maximize profits and compete à la Bertrand in the labor market, establishment specific markdowns are pinned down by the following system of equations*

$$MD_t^e = \underbrace{\frac{\frac{\eta}{\eta-1}\left[\frac{\beta+\nu}{\beta}-\Phi_t^e\right]}{1-\Phi_t^e}}_{\text{Markdown from having 1 establishment}} + \underbrace{\sum_{i\neq e,\, i\in F} \frac{\Phi_t^{e,i}}{1-\Phi_t^e}\left(MD_t^i - \frac{\eta}{\eta-1}\right)}_{\text{Additional markdown from being in a multi-establishment firm}} \tag{1.9}$$

$$\text{where} \quad \Phi_t^{e,i} = \frac{\sum_{e'} \mu_{t-1}^{e'\rightarrow i}\mu_{t-1}^{e'\rightarrow e} L_{t-1}^{e'}}{\sum_{e'} \mu_{t-1}^{e'\rightarrow e} L_{t-1}^{e'}}$$

Proof: See appendix section A.1.1.2.

Solving for the markdown of an establishment entails solving a system of equations within the firm given by equation 1.9, with the number of equations the same as the number of establishments within the firm. Apart from the Φ_t^e that captures monopsony power of the establishment, the markdown of an establishment that belongs to a multi-establishment firm also depends on the term $\Phi_t^{e,i}$. $\Phi_t^{e,i}$ depends not just on the share of workers transitioning to establishment e, but also to establishment i that belongs to the same firm. *Ceteris paribus*, if an establishment is able to attract a lot of workers, all other establishments in the same firm are able to charge a larger markdown.

If we compare two establishments with the same value of Φ_t^e that differ based on their belonging to a multi-establishment firm, the establishment that belongs to a multi-establishment firm will have a larger markdown.[30] For single-establishment firms, the markdown in equation 1.9 collapses to

[30]Note that the markdown in equation 1.9 avoids the potential cannibalization that occurs when establishments within the same firm compete with each other and drive down their markdowns.

the markdown in equation 1.8.

1.4.5 Market clearing

In the structure outlined in section 1.4.4.2, part of the firm revenue goes to wages, while the remainder going to profits. I assume that the profits accrue to local owners of establishments, who have a similar structure of preferences for consumption as workers.[31] Total income of a location n thus includes wages of workers in local establishments and the profits generated by those establishments:

$$Y_t^n = \sum_{e \in n} MD_t^e \times w_t^e L_t^e \tag{1.10}$$

$$MD_t^e \times w_t^e L_t^e = \sum_m \frac{(p_t^e \tau_{n(e)m})^{1-\eta}}{(P_t^{ms})^{1-\eta}} \kappa_s Y_t^m \tag{1.11}$$

1.4.6 General equilibrium

I now define equilibrium of the model outlined above. Given parameters $\{\nu, \beta, \eta, \kappa_s\}$, location-sector specific productivities $\{A_t^{ns}\}$, location specific home production for non-employment $\{b^n\}$, mobility frictions across establishments $\{\gamma_{ee'}\}$ initial labor allocation across establishments $\{L_0^e\}$, a sequential equilibrium of the model is labor allocation $\{L_t^e\}$, transition shares $\{\mu_t^{e \to e'}\}$, expected lifetime utility $\{V_t^e\}$, establishment level wages $\{w_t^e\}$, prices $\{p_t^e\}$, markdowns $\{MD_t^e\} \forall t$ and $\forall e, e'$ such that expected lifetime utilities satisfy equation 1.2, transition shares satisfy equation 1.3, labor across establishments evolves following equation 1.4, markdown is defined as $MD_t^e = \frac{p_t^e A_t^{ns}}{w_t^e}$ and pinned down by the system of equations in 1.9 and product markets clear according to equation 1.11.

Following Caliendo et al. [2019], a stationary equilibrium of the model is a sequential equilibrium such that all endogenous variables are constant for all time periods t.

1.5 Calibration and Baseline Equilibrium

I now turn to the calibration of the model in section 1.4 and use it to study the impact of within-firm worker mobility on labor reallocation, monopsony power and worker welfare. To this end,

[31] As outlined in Redding and Rossi-Hansberg [2017], there could be two alternatives to this structure. The first would be to introduce a global portfolio that aggregates profits of the whole economy and to give employed workers shares in this portfolio, as done in Desmet and Rossi-Hansberg [2014]. The second alternative would be to distribute profits to local workers, but this would create an inefficiency as workers moving across locations would impose an externality on profits received by other workers.

I match the key features of the Brazilian economy in 2005. I define a region in the model as a mesoregion of Brazil, yielding $N = 137$ regions, and I define three sectors: commodity, manufacturing, and services. I work with 2500 establishments, with the number of establishments in each location-sector combination proportional to those in the data. Section 1.5.3 discusses how some establishments are grouped together into multi-establishment firms. Each period in the model is a year.

1.5.1 Structure of mobility frictions

Section 1.4.2 includes establishment-to-establishment mobility frictions $\gamma_{ee'}$. I assume that the friction contains three additive elements: (i) a location switching cost $\gamma_{nn'}$ which depends on the location of establishment e and e' respectively, (ii) a sector switching cost $\gamma_{ss'}$, which depends on the sector of establishment e and e', and (iii) a firm switching friction $\gamma_{ff'}$. Spatial and sectoral frictions are common in frameworks that feature labor mobility.[32] The firm switching friction implies that it is more costly to move to another establishment within the firm of the worker than outside, conditional on a given level of location and sector switching cost. This could arise from lower search frictions within the firm, for example, because of internal labor markets[33] or portability of firm-specific skills acquired on the job (see Gibbons and Waldman [1999], for example). I further assume that spatial frictions are a function of distance $\gamma_{nn'} = \mu_0(\text{dist}_{nn'})^{\mu_1}$, with μ_1 capturing the elasticity of location switching cost to distance.

1.5.2 Parameters taken from the literature

I now describe the parameters taken from the literature. Given the annual frequency of the model, I set the discount factor $\beta = 0.97$ following Caliendo and Parro [2020]. The parameter η captures how substitutable are varieties produced by different establishments within a sector. I assume that η does not vary by sector, and assign $\eta = 8$ following Eaton and Kortum [2002] and Caliendo and Parro [2015]. I estimate κ_s, which capture the share of expenditure going to each sector, using the Inter-Country Input-Output table of the OECD using the year 2005.[34] This results in $\kappa_{commodity} = 0.14$, $\kappa_{manuf} = 0.19$ and $\kappa_{services} = 0.67$. I assume free trade in all sectors such

[32] See Caliendo et al. [2019] and Bryan and Morten [2019] for spatial frictions, and Artuç et al. [2010] for sectoral frictions. In addition, the literature on firm labor market power often defines local labor markets at either geography [Dix-Carneiro and Kovak, 2017, Kovak, 2013, Autor et al., 2013] or geography × industry [Berger et al., 2022, Alfaro-Ureña et al., 2021] suggesting substantial frictions in worker movement across locations and sectors.

[33] See Cestone et al. [2024], Bayer and Kuhn [2023], and Bagga [2022] on the importance of internal labor markets.

[34] Specifically, I use the column for Brazilian HFCE (Household Final Consumption expenditure), and divide origin sectors into commodity, manufacturing and services. I exclude sectors "Public administration and defence" and "Activities of households as employers" from total expenditure. In addition, I classify the sector "Food products, beverages and tobacco" as a commodity sector.

that the overall price index P_t^n is equalized across locations. Finally, following Bryan and Morten [2019], who estimate the elasticity of location switching cost to distance, I set $\mu_1 = 0.05$.

Table 1.4: Baseline calibration

Parameter	Description	Source/Target moment	Value
I. Externally calibrated parameters			
η	Demand elasticity	Eaton and Kortum [2002]	8
β	Discount factor	Caliendo and Parro [2020]	0.97
κ_s	Sectoral expenditure shares	OECD ICIO table 2005	See text
μ_1	Elasticity of migration cost to distance	Bryan and Morten [2019]	0.05
II. Internally calibrated parameters			
ν	Shape parameter of establishment preferences	Aggregate markdown in Brazil from Felix [2021]	0.37
$\gamma_{ff'}$	Firm switching cost	Share workers switching firms	1.2
$\gamma_{ss'}$	Sector switching cost	Share workers switching sectors	0.4
μ_0	Scalar for migration cost	Share workers migrating	0.93
SE firms	Share of firms that are single establishment	Share employment in SE firms	0.82
b_n	Home production value	Formal employment in labor force	-
A_{ns}	Location-sector productivity	Total wage bill in 2005	-

1.5.3 Internally calibrated parameters

I calibrate the remaining parameters to match the steady state outcome of the model to the Brazilian data in 2005. The solution algorithm to solve for the steady state of the model is given in appendix section A.1.3.

ν captures dispersion of worker preferences across establishments within the economy. I calibrate ν such that the aggregate wage markdown in the steady state of the model is the same as the aggregate wage markdown estimated for Brazil in Felix [2021]. Section A.1.2 derives aggregate markdown in the model as a function of establishment specific markdowns.

b_n represents the value of home production in location n which the worker obtains when they are not employed. I calibrate b_n to match the formally employed share of the labor force from the Brazilian population census of 2000 at the mesoregion level. A_{ns} represents the productivity of establishments that operate in location n and sector s. These are calibrated to match the share of total wage bill in a given location-sector combination in 2005.

I calibrate the scale parameter of spatial frictions μ_0, sector switching cost $\gamma_{ss'}$ and firm switching cost $\gamma_{ff'}$ to match the relevant values in the transition matrices of section 1.3.2. Because the level of spatial and sectoral aggregation in the model is different than that in section 1.3.2, I use the shares in appendix tables A.7 and A.9. Specifically, I calibrate μ_0 to match the share of workers that change location every year, $\gamma_{ff'}$ to match the share of workers that change firms every year,

and $\gamma_{ss'}$ to match the share of workers that change sectors every year.[35]

I classify firms into types based on the number of establishments in the firm. These types include firms with 1, 2, 5, 10 and 20 establishments. Note that there are no productivity differences across firms, which implies that two establishments in a particular location-sector will be exactly the same and differ based only on the number of other establishments in their firm. The share of firms with 1 establishment i.e. single-establishment firms is calibrated to match the share of employment in single-establishment firms in the data (59% of total employment). The share of firms of other types is based on the firm size distribution in the data. I allocate the 2,500 establishments across firms to reproduce in the model the observed probabilities that two establishments of the same firm are located in the same (i) mesoregion, (ii) state, and (iii) sector. This procedure abstracts from detailed bilateral connections between regions, but captures the aggregate features of the spatial and sectoral distribution of multi-establishment firms.

1.5.4 Baseline equilibrium

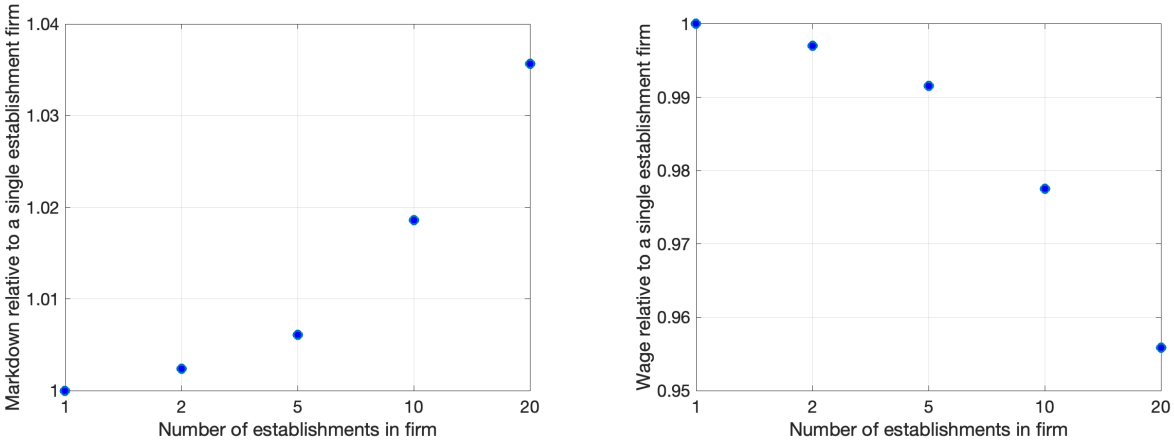
In this section, I report some of the features of the baseline steady state equilibrium. While the calibration method targets the aggregate markdown in Brazil, the level of wage and markdown for each firm type is untargeted. Figure 1.4 plots steady state markdowns and wages for establishments belonging to each firm type, relative to markdown and wage of single-establishment firms. Note that the estimates in figure 1.4 control for location-sector characteristics, with the only feature distinguishing the two establishments is the number of other establishments in their firm. On average, multi-establishment firms have a wage that is 1.7% lower[36], and markdown that is 1.5% higher than single-establishment firms. This means that markdown arising simply from firms being multi-establishment explains 10% of the unconditional difference between multi and single-establishment firm markdown identified in Yeh et al. [2022].[37]

[35]Note that while parameters μ_0, $\gamma_{ss'}$ and $\gamma_{ff'}$ allow me to match the share of workers that change locations, sectors and firms every year respectively, it still does not guarantee that I match the share of migration or sectoral changes that occur within the firm. To do that, I add two more parameters that change the size of $\gamma_{ss'}$ and $\gamma_{ff'}$ and allows me to match the share of migration and sectoral reallocation that happens within firms in the model.

[36]This finding echoes Jarosch et al. [2024], who show that larger firms possess size-based market power: because workers are more likely to re-encounter the same firm, outside options are weaker when bargaining with bigger employers, leading to lower wages.

[37]Unconditional difference in the markdowns of multi and single-establishment firms could reflect productivity differences between firms. Such differences could be controlled for by proxies such as firm size. However, while Yeh et al. [2022] report that markdowns of establishments of multi-establishment firms are larger than those of single-establishment firms even controlling for firm size, they do not report the actual coefficient of this result.

Figure 1.4: Equilibrium markdowns and wages by number of firm establishments

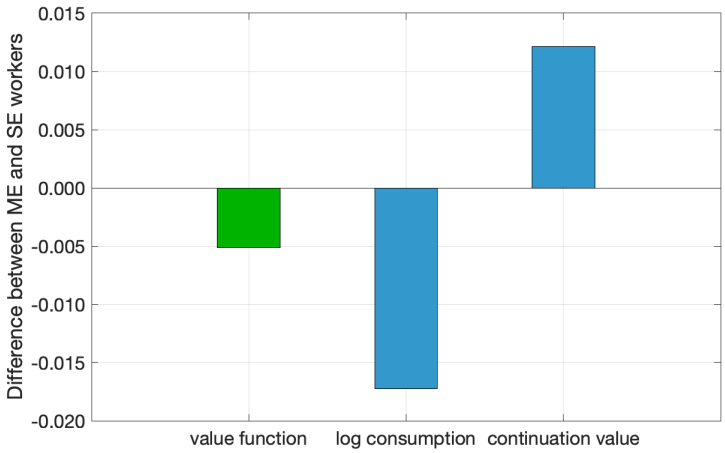


(a) Markdowns (b) Wages

Note: These figures plot markdown and wages by number of firm establishments in the steady state equilibrium. Both figures control for location $\times$ sector fixed effects, with values driven solely by number of establishments in the firm.

How does the overall welfare of multi-establishment workers compare with welfare of single-establishment workers? Figure 1.4 panel (b) would suggest that multi-establishment workers are worse off as their wages are 1.7% lower relative to single-establishment workers. However, note from equation 1.2 that the expected lifetime utility of the worker depends not just on the real wage offered by their current establishment, but also the continuation value of working in that establishment. The continuation value of multi-establishment workers is higher, as such workers face fewer frictions to some of the other establishments in the economy, specifically those that belong to the same firm as their current establishment. This tradeoff between lower wage and higher continuation value is captured in figure 1.5. If we only focus on the wage differential, multi-establishment workers will have welfare that is 1.7% lower on average relative to a single-establishment worker. However, the continuation value of multi-establishment workers is larger, and compensates for 70% of lost wages.

Figure 1.5: Comparing welfare in steady state: single vs multi-establishment workers



Note: Figure shows the difference in log consumption, continuation value and value function of multi and single establishment firms. The figure controls for location × sector fixed effects, with difference driven solely by multi-establishment status.

1.5.5 Model validation

While the steady state outcome of the model is used for calibration, in this section, I check dynamic response of the model to negative productivity shocks as a model validation exercise. As shown in fact 3 in section 1.3.3.2, following closure of establishments, workers of multi-establishment firms are less likely to drop out of the labor force, and more likely to migrate. This is partly explained by reallocation of multi-establishment workers to other establishments in the same firm. Panel (b) of figure A.18 shows the probability that location of multi-establishment worker is different than their location in the period before establishment closure, relative to that of a single-establishment worker who also faced an establishment closure.

The model does not allow me to follow individual workers, precluding from doing the same exercise in the model. However, I closely approximate the establishment closure shock by introducing an unexpected negative productivity shock in a given location and tracking how employment in establishments of multi-establishment firms evolves relative to employment in establishments of single-establishment firms in that location. Panel (a) of figure A.18 shows the difference in relative employment of single and multi-establishment firms in the shocked location, following the shock.[38] While panel (a) and (b) of appendix figure A.18 capture slightly different objects, they still capture the same underlying phenomenon: following a negative shock, workers of multi-establishment firms migrate first, exploiting opportunities within their firm. This is followed by migration of

[38]The size of the shock is calibrated such that the differential impact between single and multi-establishment employment in the model right after the shock is the same as in the data.

single-establishment workers who migrate a few periods after the shock, such that the difference reduces over time. Panel (a) and (b) of appendix Figure A.19 show the actual level of employment of multi and single-establishment firms in the shocked location (instead of the difference), along with evolution of markdowns in the shocked location.

1.6 Multi-establishment firms and negative shocks

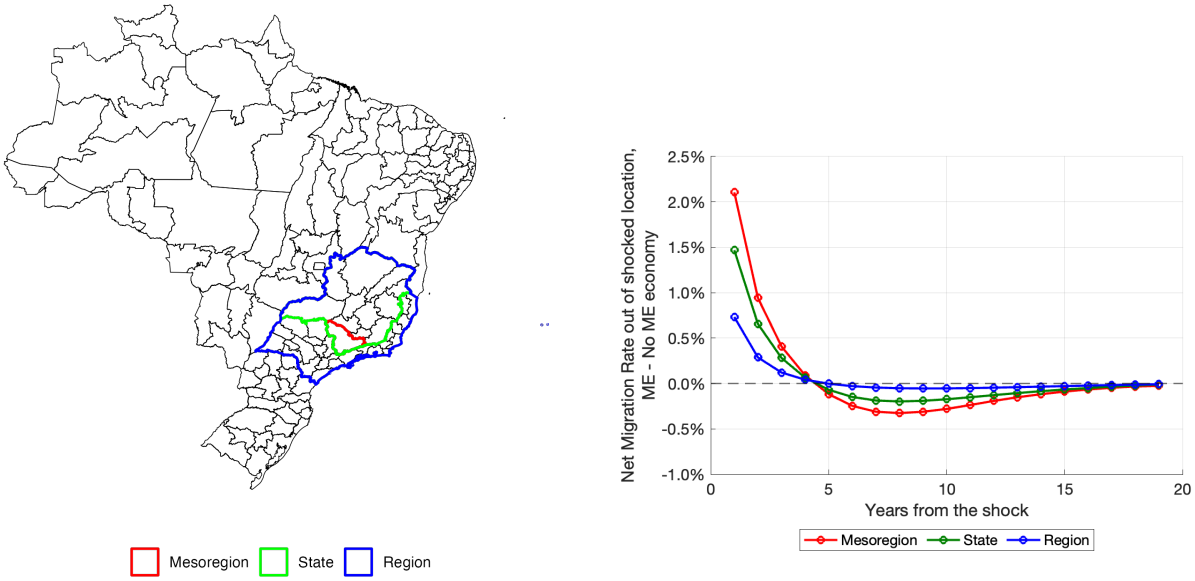
Figure 1.5 suggests that on average the welfare of multi-establishment workers is lower than that of single-establishment workers. However, that speaks to the steady state equilibrium. In the face of negative shocks, it may be valuable for workers to be in a multi-establishment firm, as they can potentially transfer to unaffected establishments of their firm. Multi-establishment firms could also be valuable for the overall economy, if they can reallocate workers away from negatively affected locations or sectors more effectively than single-establishment firms.

In this section, I evaluate the importance of multi-establishment firms for both workers and the overall economy in the face of negative shocks. To do this, I introduce negative productivity shocks at varying levels of geography, and compare responses in the baseline economy with multi-establishment firms to an economy which consists of only single-establishment firms. Other features of the two economies are exactly the same, with the same set of parameters, the number and distribution of establishments, location-sector specific productivities, and the value of home production. Varying the geography allows me to study whether the importance of multi-establishment firms depends on the scope of the shocks. I assume that the economy reaches its new steady state 20 years after the shock.

1.6.1 Impact on worker reallocation

Figure 1.6 shows the three geographies hit with an unexpected negative 20% productivity shock. I first shock the mesoregion Sudoeste De Minas, followed by the state of Minas Gerais and then all of the South East region of Brazil. I assume that the economy was in the steady state at the time of the shock. Figure 1.6 panel (b) shows the difference in the migration response in the shocked location between the economy with and without multi-establishment firms. In all three cases, the migration response in the period after the shock is larger in the economy with multi-establishment firms, as these firms allow their workers to move to other establishments in the same firm. However, after the 4th post shock period, the migration rate out of the shocked location is larger in the economy without multi-establishment firms. The multi-establishment economy front-loads the migration of workers out of shocked locations, moving workers out of the shocked location quicker than the no multi-establishment economy.

Figure 1.6: Productivity shock and net migration



(a) Shocked locations

(b) Net migration out of shocked location

Importantly, this feature weakens with the geographic scope of the shock. When only a mesoregion is shocked, 2.1 percentage point more workers migrate in an economy with multi-establishment firms relative to an economy without multi-establishment firms. This difference narrows to 1.5 p.p. when the shock is at the state level, and 0.7 p.p. when the shock is at the regional level. This is because multi-establishment firms have lower potential to reallocate workers when a larger share of their establishments are being affected.[39]

Apart from moving workers out of shocked locations, a multi-establishment economy is also valuable in limiting the transition of workers into non-employment after the shock. Appendix figure A.21 shows transitions to non-employment of workers in shocked location after the shock. Based on the geography of the shock, the transition to non-employment is 0.5-0.7 p.p. lower in the economy with multi-establishment firms relative to the economy without multi-establishment firms. This headline difference masks the large heterogeneity that exists across workers by firm type. Panel (a) of figure A.22 shows that a worker working in a firm with 20 establishments is 3.5 p.p. less likely to go into non-employment than a worker working for a single-establishment firm following the mesoregion shock.[40]

[39]Figure A.20 shows the actual level of migration out of the three shocked locations (as opposed to the difference in panel (b) of figure 1.6).

[40]To parallel the establishment closure shock in section 1.3.3, I also hit the mesoregion with a 99% productivity shock. Panel (b) of figure A.22 shows worker transitions after the shock. A worker in a firm with 20 establishments is 15 p.p. less likely to transition into non-employment relative to a single establishment worker.

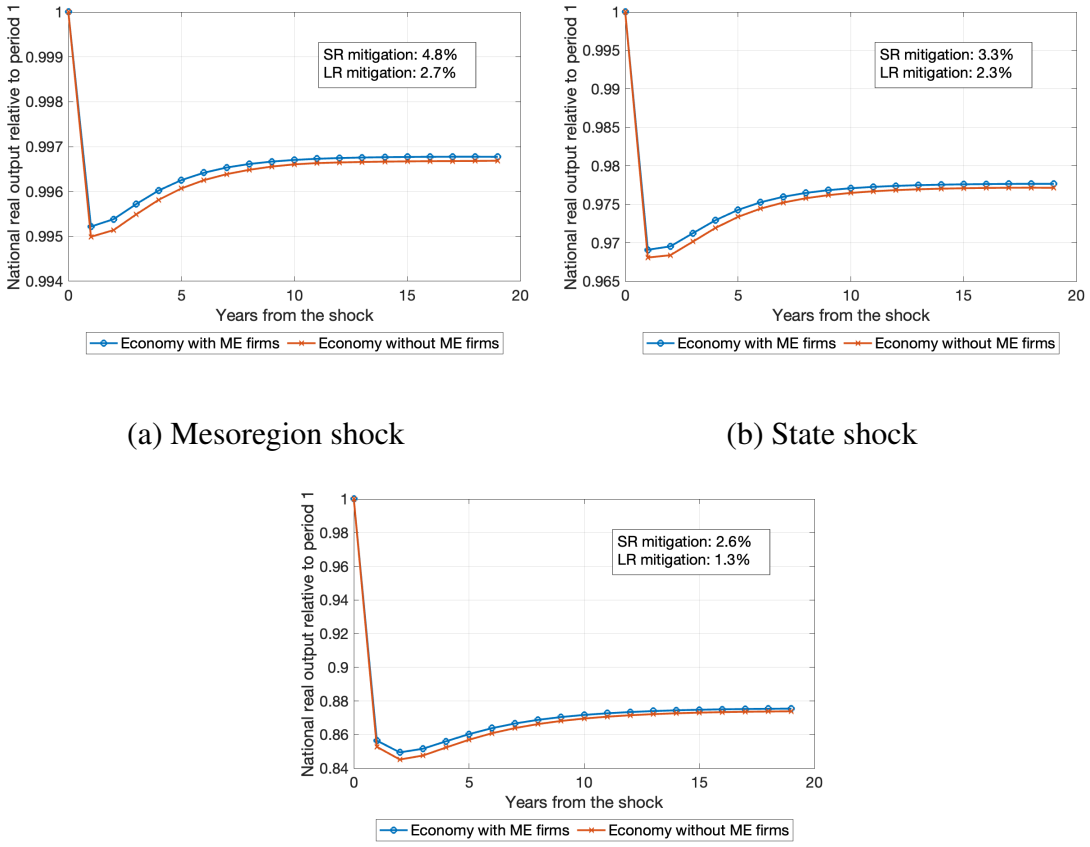
1.6.2 Impact on aggregate output

Following a negative location shock, a multi-establishment economy is able to reallocate workers out of shocked location and limit transitions into non-employment relative to a single establishment economy. How valuable is this ability from the perspective of aggregate output?

Figure 1.7 shows the impact of the three negative shocks on aggregate output in the country. In both economies, the shocks have a large negative impact on aggregate output. However, the multi-establishment economy is able to mitigate part of the negative impact: in the short run, without multi-establishment firms, the negative shock would lead to output that is 4.8% lower when the shock affects the mesoregion. When the shocks are at state and region level, the mitigation amounts to 3.3% and 2.6% respectively. Again, the importance of multi-establishment firms declines with the scope of the shock, as their ability to reallocate workers weakens as a larger share of the economy (and thus a larger number of establishments within each firm) is negatively affected. The mitigation in the long-run is lower than the short run, as the single-establishment economy partially catches up in terms of moving workers out of the shocked location, as shown in panel (b) of figure 1.6.

I test the sensitivity of the above results by also varying the size of the shock. Appendix Table A.21 shows both the long and short run mitigation with 10, 20 and 30% productivity shocks. In general, while the level of mitigation decreases with the scope of the shock, it increases with the size of the shock.

Figure 1.7: Impact of negative productivity shocks on aggregate output



(a) Mesoregion shock

(b) State shock

(c) Region shock

1.7 Conclusion

This paper studies how large multi-establishment firms shape worker mobility and welfare by enabling reallocation across space and sectors. Using matched-employer employee data from Brazil, I showed that a large share of aggregate reallocation of workers across space and sectors happen within firms. In addition, I showed that multi-establishment firms provide insurance against negative shocks to their workers, while allowing them to exploit positive shocks, through the channel of internal reallocation.

I then developed a dynamic economic geography model that incorporates (i) the distinction between multi and single establishment firms and (ii) establishment specific endogenous wage markdowns. In the model, multi-establishment firms offer workers "amenity" of lower mobility frictions to other establishments of the firm. Firms internalize that workers value this amenity and offer lower wage and charge large wage markdowns. In the model calibrated to Brazilian

data, I find that multi-establishment firms offer 1.7% lower wages to their workers and charge a 1.5% larger markdown. I also showed via counterfactual exercises that multi-establishment firms are valuable in mitigating the impact of negative shocks on output, as they reallocate workers internally in response to shocks, and away from shocked locations.

These findings highlight several avenues for future work. First, within firm movement is one way in which large firm enable reallocation across space and sectors. However, firms potentially play an important role in reducing information frictions for its workers with its network of establishments. Workers could learn about other locations or sectors through their firm and decide to migrate. This channel is not the focus of this paper and would further strengthen the importance of large firms in enabling worker reallocation. Second, industrial policy and place-based subsidies have received renewed interest from policymakers. To what extent should such policies target small or large firms? A framework like in this paper could be extended to answer such questions and evaluate the impact of those policies on worker reallocation, firm market power and wages. Finally, there has been renewed focus on the labor market implications of merger policies (see Berger et al. [2025]). The framework of this paper could be extended to evaluate some of the tradeoffs, where mergers lead to higher market power, but also better worker reallocation and responsiveness to shocks.

CHAPTER 2

Adaptation to Climate Risk: Evidence from Cyclones and Flooding in Bangladesh

Abstract

I evaluate the importance of adaptation in dealing with increase in climate risk. Using long-term data on cyclones and flooding in Bangladesh between 1960 and 2010, I study adaptation along two margins: changes in crop choices, and reallocation of workers across sectors. I find that an increase in propensity of both cyclones and floods affect crop choice, but only cyclones affect sectoral employment, shifting employment out of agriculture. I develop a structural model to study the welfare implications of adaptation and calculate the value of adaptation i.e. how much worse the economic impact of rising climate risk would be if these adaptation channels were unavailable. In a scenario where both flooding and cyclone propensity double relative to the 2000s average, the absence of adaptation would result in welfare losses that are 29% larger than in a world with adaptation.

2.1 Introduction

Climate change is expected to worsen the frequency and intensity of extreme weather events such as floods, droughts, hurricanes and heatwaves (EPA, 2025). This will lead to an increase in the downside risks that economic agents are exposed to. A key question is: how important is adaptation in dealing with the adverse effects of climate change? If adaptation is important, any projections about the economic implications of climate change will likely overestimate its impact if they fail to account for how economic agents respond to worsening climate conditions around them. In addition, adaptation opens up a role for policymakers to influence the economic costs of future climate risk. If there are frictions to adaptation, reducing those frictions could alleviate the passthrough of climate risk to the economy.

Using long-term data on flooding and cyclone incidence in Bangladesh from 1960 to 2010, I study how increases in climate risk lead to *in-situ* adaptation along 2 margins: within agriculture changes and reallocation of workers across sectors. These two margins are especially relevant for developing countries, where the share of employment in the agriculture sector is large and the ability to relocate to other regions may be limited by high mobility frictions. To study adaptation along these two margins, I collect data from agriculture and population census publications between 1981 and 2011 at the level of Bangladeshi upazilas, which are the third tier of administration in Bangladesh. Given its frequent exposure to extreme weather events, Bangladesh provides an ideal setting to study medium- to long-term adaptation to climate risk.[1]

In the empirical section, I document how crop choice and sectoral employment in agriculture respond to increase in climate risk, by exploiting changes in flooding and cyclone propensity over 10 or 12-year periods. For crop choice, I find that for an average crop, an increase in flooding propensity by 0.1 meter during a crop's season reduces the land share used for that crop by 7.9 percentage points, while an increase in cyclone propensity by 10 kmph during a crop's season reduces the land share used for that crop by 2.3 percentage points. With respect to sectoral employment, while I find that an increase in cyclone propensity by 10 kmph reduces the share of workers in agriculture by 1.5 percentage points, an increase in flooding propensity has a marginally positive but statistically insignificant effect on the share of workers in agriculture.

Guided by the empirical results, I develop a general equilibrium model that incorporates decisions along the two margins of adaptation. Importantly, the model features damage functions that translate cyclone and flooding propensity into output losses, with the parameters of the damage functions calibrated to match the adaptation responses in the empirical section. Using the calibrated model, I conduct counterfactual exercises to evaluate the impact of future increases in climate risk and calculate the value of adaptation — that is, how much worse welfare would be if climate risk increases but adaptation is not possible.

In the scenario where cyclone and flooding propensity doubles relative to the 2000s average, welfare declines by 3.85% in a model without adaptation but declines by 2.98% when adaptation is allowed, implying a value of adaptation of 29.2%. I find that the value of adaptation depends on two features of future climate shocks: their intensity and their correlatedness across crops and regions. The value of adaptation increases with the intensity of future shocks but decreases with their correlatedness across crops and regions. While the empirical section of this paper does not focus on migration as an adaptation channel, I extend the baseline model to allow for migration, subject to a migration elasticity found in the literature in the context of developing countries. When migration is an additional channel of adaptation, the value of adaptation increases from 29.2% to 41.1%. I test the robustness of these findings by varying the functional forms of damage functions,

[1] Bangladesh is consistently placed among the most climate vulnerable countries in the world by the UN.

adjusting parameter values, and altering the intensity and correlatedness of future climate shocks.

This project relates to the evolving literature on responses to climate shocks and the importance of such responses in mitigating the impact of climate change on welfare. Most papers focus on a subset of rainfall, temperature, flooding, drought or cyclone shocks, and study their impact on agriculture, sectoral reallocation, migration, firm performance, etc. Kala et al. [2023] provide a brief overview of this literature. The seminal papers studying the effects of climate change on agriculture and sectoral reallocation, the outcomes of interest in this paper, include Costinot et al. [2016] and Conte et al. [2021] respectively.

I contribute to the literature in three ways. First, the long time span of the climate data and the frequency of cyclone and flooding in Bangladesh provide an ideal setting to estimate medium-term adaptation responses to climate shocks. Many studies exploit short term variation in weather, as opposed to medium-term shifts in the propensity of climate shocks [Guiteras, 2009, Jessoe et al., 2018, Colmer, 2021]. A caveat of this approach is that short-term responses provide information about the impact of weather shocks, which may be different from the response to medium to long-term shifts in climate risk. As mentioned in Burke and Emerick [2016], exploiting longer-term shifts in climate risk provides a better estimate of how agents react to sustained changes in shock propensity due to climate change.

Second, the existing literature on the economics of climate change has often focused on using changes in precipitation and temperature as proxies for worsening climate conditions. This includes Burke and Emerick [2016], who focus on US agriculture and Liu et al. [2021], who focus on sectoral employment shifts and migration in India. While temperature and precipitation changes are important mechanisms through which climate change will be experienced, another channel is the increasing likelihood of extreme weather events like floods, droughts, and hurricanes. By relating the empirical results to the literature, I provide evidence that extreme weather events do not necessarily have the same impact as changes in temperature and precipitation.[2]

Finally, the existing literature has often focused on how a specific adaptation margin reacts to an increase in climate risk. For example, Nath [2020] focuses on agriculture, Colmer [2021] focuses on sectoral reallocation and while Peri and Sasahara [2019] focus on migration as a response to climate shocks. I bring together two key decisions under the same framework: (i) which sector to work in and (ii) if working in agriculture, which crops to grow. In the model, an extension also incorporates migration as a third potential channel of adaptation.[3] Looking at the adaptation channels in isolation might ignore the complementarities and linkages in decision making across

[2]In their respective settings, Mueller et al. [2014] and Boustan et al. [2012] talk about the heterogeneous effects across different types of climate shocks.

[3]I do not have empirical results on migration due to lack of data on origin of individuals in each upazila or a share of residents who are migrants. For a study on migration in response to flooding in the context of Bangladesh, see Patel [2024] here.

the different channels, or how the presence of a channel of adaptation affects the importance of others.

The rest of the paper is organized as follows. Section 2.2 describes the data sources and section 2.3 presents the empirical results on the importance of the two adaptation channels. Section 2.4 presents the structural model, followed by section 2.5 that parameterizes the model and section 2.6, which uses the model to answer counterfactual questions and calculate the value of adaptation. Section 2.7 concludes the paper.

2.2 Data

Agriculture census: I collect data from the Agriculture Census of Bangladesh for the years 1984, 1996 and 2008 from the Zila series books published by the Bangladesh Bureau of Statistics (BBS). The census provides information on land use by crop, net cultivated area, share of irrigated land, number of agricultural holdings, etc. for all upazilas of Bangladesh. To deal with changing boundaries of upazilas over time, I aggregate agriculture data to upazilas as they existed in 1984, resulting in 460 upazilas.

Population census: I use population census data from the years 1981, 1991, 2001 and 2011. I collect the data for 1981 and 2011 using the Zila series books published by BBS. For 1991 and 2001 censuses, I use the 10% samples from IPUMS. The population census has data on the age structure, sectoral employment, labor force participation, etc. at the upazila level. To deal with changing boundaries of upazilas over time, I aggregate population data to upazilas as they existed in 1981, resulting in 451 upazilas.

Water level data: Due to the history of flooding in Bangladesh, the country has a number of stations along the main rivers that record the water level on a daily basis.[4] I collect this data from Institute of Water Modelling (IWM) of Bangladesh, who shared the monthly maximum and minimum water level records for 182 stations from across the country. I use this data to construct monthly flood maps at the upazila level from January 1951 to December 2020 that report flood level in meters. The methodology used to construct the flood maps is described in more detail in section B.1.1 in the appendix.

Cyclone data: Data on cyclone landfalls from 1960 to 2020 is collected from the World Bank.[5] I use the information on the cyclone path and windspeed to construct monthly cyclone incidence at the upazila level. The methodology used to construct the cyclone shocks is described in more

[4]Water level stations are a more accurate proxy for flooding in Bangladesh than rainfall. Due to its geographic location as a delta of two major rivers, the country can experience flooding without any rain due to upstream runoff [Philip et al., 2019].

[5]The dataset is called Cyclonic Storm Landfalls In Bangladesh, West Bengal And Odisha 1877-2016 and can be accessed here.

detail in appendix section B.1.2.

Other data: The Household Income and Expenditure Survey (HIES) 2010 is used to obtain expenditure shares on different commodities and is to parameterize the utility function. Additional geographic and climate data used to construct monthly flood maps includes data on elevation and rainfall. Elevation data comes from Shuttle Radar Topography Mission (SRTM) while monthly rainfall data for Bangladesh comes from Dewan et al. [2022], who use multiple sources to collect data from 1901 to 2018 at the level of a grid defined at 2 decimal places.[6] Finally, a road network map of Bangladesh is obtained from *Logistics Cluster*, and used to implement the Fast Marching Method (FMM) to calculate bilateral trade costs for upazilas.[7]

Table B.1 and B.2 in the appendix summarize the key statistics from the agriculture and population census respectively. In the agriculture sector, there was a large increase between 1984 and 2008 in the share of land that is irrigated, and a decline in the average size of the agricultural landholding. Aman rice remained a major crop across the three years, but there was an increase in the share of land growing Boro rice, the variety grown in the winter season. From the population census, we see an increase in population density of the country and a decline in the share of labor employed in the agriculture sector.

2.3 Empirical Results

In this section, I present the reduced-form results relating to the impact of an increase in flooding and cyclone propensity along two adaptation channels: crop choice and sectoral employment choice. For both channels, I use a panel approach to identify plausibly causal estimates, in line with the recent climate economics literature [Dell et al., 2014]. The panel approach relies on the idea that controlling for the upazila and region-time fixed effects, the variation induced by decadal shifts is quasi-random. To complement the panel approach, I replicate the analysis using first differences, which works with decadal changes in the dependent and independent variables instead of levels.

The cyclone and flooding data is at the monthly level, but the outcome variables are every 12 years in the case of agriculture census data or 10 years in the case of population census data. To aggregate monthly climate shocks to yearly level, I use the maximum observation within each year. For example, the highest monthly observation of flooding in an upazila for 1995 defines the flooding shock for the upazila for 1995. When working with crop seasons instead of annual seasons, the maximum observation during the crop season is taken as the shock (table B.3 in the appendix shows the cropping seasons for the six major crops in Bangladesh). The climate shocks

[6] Each grid cell represents an area of roughly 1.11×1.11 kilometers.

[7] The road network map can be accessed here.

are then averaged across the previous 10 or 12 years, resulting in average flooding and cyclone propensity in the previous 10 or 12 year period. Plots B.3 and B.4 in the appendix show the upazila level distribution of the average flood and cyclone shocks over the previous 12 years for 1984, 1996 and 2008.

2.3.1 Crop choice and climate shocks

To identify the impact of increase in cyclone and flooding propensity on crop choice, I use the specification in equation 2.1. The panel includes five main crops of Bangladesh: Aus rice, Aman rice, Boro rice, Wheat and Jute.[8]

$$\text{Sh land}_{u,c,t} = \beta_{fl,crop}\text{flooding}_{u,c,t-12:t-1} + \beta_{cyc,crop}\text{cyclone}_{u,c,t-12:t-1} + \gamma_{D,t} + \theta_{u,c} + \alpha_{C,t} + \varepsilon_{u,c,t} \tag{2.1}$$

$\text{Sh land}_{u,c,t}$ is the share of Net cultivated area[9] used to grow crop c in upazila u at time t. $\text{flood}_{u,c,t-1}$ represents the average level of flooding (in meters) in upazila u during the season of crop c in the past 12 years, while $\text{cyclone}_{u,c,t-1}$ represents the average cyclone windspeed (in 100 kmph) experienced by upazila u during the season of crop c in the previous 12 years. $\gamma_{D,t}$ are division-year fixed effects that control for unobserved region-specific confounding factors over time, where divisions are the first unit of administration in Bangladesh. $\theta_{u,c}$ are upazila-crop fixed effects and control for any time invariant characteristics for growing crop c in upazila u, such as how productive an upazila is in growing a particular crop. $\alpha_{C,t}$ represents crop type-time fixed effects and control for changes in national or world prices of different crops, changing preferences or changing production technology common to crop types. $\beta_{fl,crop}$ and $\beta_{cyc,crop}$ are the coefficients of interests that measure the extent to which increases in average flooding and cyclone propensity changes land share devoted to each crop. Standard errors are clustered at the level of upazila-year.

Table 2.1 presents results for equation 2.1.[10] Column 1 includes Division-year fixed effects while column 2 does not. Based on column 1, an increase in propensity of flooding by 0.1 meter during a crop's season decreases the share of land used to grow the crop by 7.9 percentage points, while an increase in cyclone propensity by 10 kmph reduces the share of land used to grow the crop by 2.3 percentage points. The share of land used to grow a crop could be affected not just by

[8]Potato is excluded as cropped area for Potato is not available in 1984. These 5 crops accounted for 79.4% of Gross cropped area in 1984, 82.6% in 1996 and 70.7% in 2008. These 5 crops along with Potato are considered 'major crops' by Bangladesh Bureau of Statistics (BBS) in its annual publications.

[9]Net cultivated area is the total amount of land used for agriculture in a given year. This is different than Gross cropped area, which is the sum of area planted across all crops.

[10]Following Burke and Emerick [2016], table B.4 in the appendix reports the results of specification of equation 2.1 in first-differences, instead of a panel specification.

Table 2.1: Crop choice and climate shocks

Dependent Variable:	Land share for crop in Net cultivated area			
	(1)	(2)	(3)	(4)
Flooding level (m)	-0.794***	-0.741***	-0.864***	-0.832***
	(0.108)	(0.106)	(0.109)	(0.109)
Cyclone windspeed (100 kmph)	-0.234**	-0.187**	-0.342***	-0.189**
	(0.096)	(0.094)	(0.101)	(0.094)
Flooding level out season (m)			0.326***	0.310***
			(0.087)	(0.089)
Cyclone windspeed out season (100 kmph)			-0.408***	-0.267***
			(0.093)	(0.082)
Division-year FE	Yes	No	Yes	No
Upazila-crop FE	Yes	Yes	Yes	Yes
Crop type-year FE	Yes	Yes	Yes	Yes
Observations	6,765	6,765	6,765	6,765

Notes: The panel includes years 1984, 1996, and 2008. Standard errors clustered at the upazila-year level are reported in parentheses. Only upazilas with non-missing observations in all three years are included. Observations are weighted by the average net cultivated area of the crop in the upazila across the three census years. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

flooding and cyclone propensity during the season of the crop, but also their propensity outside the season.[11] To further isolate the effect of in-season climate shocks on crop choice, column 3 and 4 of table 2.1 controls for average flooding and cyclone incidence outside the season of the crop over the previous 12 years. Focusing on column 3 of table 2.1, the absolute value of the coefficient increases on the inclusion of these controls.[12]

I test the robustness of the baseline results in table 2.1 in a number of ways. First, the impact of the flooding and cyclones on crop choice may be nonlinear, and only kick in after a certain level of intensity. To address this, I define binary indicators for flooding and cyclone shocks. A crop in an upazila faces a flood in a particular year if the biggest flood during the crop's season in that year in the upazila is more than 0.5 meters - an often used threshold for defining moderate flooding in Bangladesh [Islam et al., 2019]. Similarly, I define a cyclone based on whether the highest windspeed during the crop's season exceeded 61 kmph, in line with the definition of hurricanes based on Yang [2008]. I then average the shocks over the previous 12 years to align cyclones

[11] Two upazilas with the exact same characteristics, facing the same prices and with the same level of flooding during Aman rice season could still have different land shares for Aman based on how severe the flooding and cyclone shocks are during the seasons of other crops.

[12] The coefficients on flooding outside a crop's season are positive in column 3 and 4 of table 2.1, but negative on cyclone outside the season. One possible explanation is that cyclones lead to a reallocation of land toward crops not included among the five main crops in table 2.1. To test this, I examine how the share of land allocated to other crops responds to flooding and cyclone shocks. Table B.5 in the appendix indicates that while greater flooding propensity reduces land allocated to other crops, greater cyclone propensity increases it. This suggests that flooding leads to reallocation among the five main crops themselves, whereas cyclones shift land use toward other crops.

and flooding with the agricultural census data outcomes. The resulting variable represents the probability that a given upazila-crop combination experienced a flood or cyclone in the past 12 years. Table B.6 in the appendix reports the regression results using these binary indicators, which are largely consistent with those in table 2.1.

Second, I run specifications for all five crops individually, to check if particular crops are more affected by flooding and cyclones. As can be seen in table B.7 in the appendix, Aman rice is the most affected crop among the five selected crops. This is unsurprising, as Aman is grown from July to November, coinciding with both the flooding and cyclone seasons (see figure B.5). Indeed, Aman rice is the only crop that is grown in the middle of the flooding season. Other crops could be exhibiting limited passthrough of climate shocks either because the shocks are very small during the crop's season[13], or that adaptation out of those crops has already happened in upazilas exposed to those shocks, such that further increases in climate shocks has limited effects. That is not the case with Aman rice, as it is widely grown: 49% of Net cultivated area was used to grow Aman rice in 2008.

There are few papers in the literature identifying the impact of increasing climate risk on crop choice, especially climate risk arising from cyclones and floods. Burke and Emerick [2016] find a large negative impact of decadal changes in temperature and precipitation on maize and soy yields in the US. However, they find limited adaptation in terms of the crops farmers grow. Auffhammer and Carleton [2018] show in the context of India that areas with higher crop diversity of planted area display measurably more drought resilience, but not necessarily diversity increasing in response to drought risk. The estimates from table 2.1 empirically support the findings in Costinot et al. [2016], who use a general equilibrium model to estimate that climate change would result in a 0.26% reduction in global GDP through its effects on crop yields, but the reduction would be 0.78% if farmers could not adjust their crops, emphasizing how critical crop adjustment is in mitigating climate change.

2.3.2 Sectoral employment and climate shocks

The second adaptation channel I study is structural change: if the propensity of flooding or cyclones increases in an upazila, one way individuals can adapt is change the sector they work in. *A priori*, the impact of climate shocks on sectoral employment is ambiguous. On one hand is the "food problem" interpretation of Gollin et al. [2007], where developing countries specialize in agriculture despite low productivity because of the importance of food. If this interpretation is correct, then an increase in flooding or cyclone propensity will reduce agriculture productivity, making more people work in agriculture due to the non-homotheticity involved in consumption of

[13]For example, wheat is grown and harvested from mid-November to March, thus avoiding both the flooding and cyclone seasons.

agricultural goods. This effect will be exacerbated in an environment of high trade costs, which would reduce the ability of an upazila to import food from elsewhere. On the other hand is the relative productivity interpretation, where individuals shift away from agriculture as it becomes less productive compared to the non-agriculture sector. To estimate the effect of climate shocks on sectoral employment, I use the following specification:

$$\text{Sh agri employment}_{u,t} = \beta_{fl,emp}\text{flooding}_{u,t-10:t-1} + \beta_{cyc,emp}\text{cyclone}_{u,t-10:t-1} + \gamma_{D,t} + \theta_u + \varepsilon_{u,t} \tag{2.2}$$

Table 2.2 shows the impact of an increase in propensity of flooding and cyclones on agricultural employment.[14] Since the population census data exists at 10 year intervals, $\text{flood}_{u,t-1}$ and $\text{cyclone}_{u,t-1}$ represent the average flooding (in meters) and average cyclone windspeed (in 100 kmph) experienced by upazila u in the previous 10 years. θ_u is upazila specific fixed effect, controlling for time-invariant characteristics of an upazila. $\gamma_{D,t}$ are division-year fixed effect and control for unobserved region-specific confounding factors over time.

In column 1 of table 2.2, which includes both upazila and division-year fixed effects, while an increase in propensity of cyclones by 10 kmph decreases the share of workers that work in the agriculture by 1.5 percentage points, I find that an increase in the propensity of flooding has a marginally positive, but statistically insignificant effect on share of workers in agriculture. Using column 1 of table 2.2, which constructs the climate shocks based on binary outcomes, a 10 percentage point increase in the probability of being hit with a cyclone decreases agricultural employment share by 1.7 percentage points.

One interpretation of this result is that while an increase cyclone propensity worsens outcomes for the agricultural sector, this need not be true for flooding. Unlike cyclones, floods can have offsetting benefits: receding waters deposit nutrients and sediment, boosting post-season productivity [Wright et al., 2015]. The negative effects of flooding during the season and positive effects outside the season could cancel each other out. Another difference lies in the timing of flooding and cyclone shocks. An increase in flooding only affects one growing season: that of Aman rice. It is possible for farmers to avoid the flood season and switch to other crops. In contrast, as shown in figure B.5 in the appendix, increases in cyclone propensity would affect two distinct seasons: April-May and October-November. This decreases the potential to transition to other crops, and could explain why workers simply move out of agriculture as cyclone propensity goes up.

I find some evidence of this mechanism: table B.10 in the appendix runs a specification similar to equation 2.2, but with cropping intensity as the dependent variable. Cropping intensity is calcu-

[14] Table B.8 in the appendix shows the results of the specification 2.2 in first differences, by taking differences over 10 year intervals. Table B.9 shows specification 2.2 with log of the agriculture employment share as the dependent variable, instead of level of the share. Both alternative specifications yield estimates comparable to table 2.2.

Table 2.2: Agricultural employment and climate shocks

Dependent Variable:	Agricultural employment share			
	(1)	(2)	(3)	(4)
Flooding level (m)	0.032	0.039		
	(0.036)	(0.032)		
Cyclone windspeed (100 kmph)	-0.152***	-0.072***		
	(0.033)	(0.024)		
Flooding binary			-0.016	-0.003
			(0.018)	(0.018)
Cyclone binary			-0.170***	-0.104***
			(0.032)	(0.025)
Division-year FE	Yes	No	Yes	No
Upazila FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes
Observations	1,804	1,804	1,804	1,804

Notes: The panel includes years 1981, 1991, 2001, and 2011. Standard errors clustered at the upazila level are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

lated as the ratio of Gross and Net cultivated area, and is a measure of how many crops per unit of land are grown in an upazila in a calendar year. Based on column 1 of table B.10 in the appendix, an increase in cyclone propensity by 10 kmph implies that 0.176 fewer crops are planted per unit of agricultural land. However, increases in flooding propensity does not lead to a statistically significant change in the number of crops planted per unit of land. Second, I use additional data from the agriculture census to see if the patterns are consistent with the result in table 2.2. If increase in cyclone propensity shifts people out of agriculture but not flooding, I should also see agricultural land decline in a similar way. Table B.11 in the appendix shows that increase in cyclone propensity indeed reduces total agricultural land, but not flooding.

Table 2.2 would suggest that the relative productivity interpretation holds, with people moving out of agriculture as it becomes less productive compared to the non-agriculture sector. Liu et al. [2021], which also focuses on decadal shifts in agricultural employment in the context of India, find that an increase in temperature increases the share of workers in agriculture, in line with the food problem interpretation. However, there is a difference in the nature of the climate shocks being analyzed: the damage from flooding and cyclones can take on extreme proportions, which is unlikely to happen with precipitation and temperature, where the damage functions are flatter [Agnolucci et al., 2020]. If agents are risk-averse, the possibility of an extreme event would shift them away from crops where such events are likely. While these second-order effects are potentially interesting in differentiating the impact of different climate shocks, I do not pursue them in this paper.

2.4 Model

Section 2.3 demonstrates that switching crops and sectors is an important channel through which individuals adapt to an increase in the propensity of climate shocks. This section develops a quantitative general equilibrium model that incorporates decisions along these two margins of adaptation. The model provides a framework to study the welfare impact of adaptation, and incorporates differences across upazilas in terms of their productivity, trade costs and heterogeneity across plots. There is no migration in the baseline model, but I extend the model to allow for migration in section B.4.1 of the appendix.

There are N upazilas in the model, indexed by u, n. K_u is the total amount of land in upazila u and L_u is the total population. There are $c \in C$ crops, with each upazila producing its own unique variety of each crop. Both manufacturing and agricultural goods are tradable subject to symmetric iceberg trade costs τ_{un}.

2.4.1 Consumer preferences

Representative consumers get utility from consumption and supply labor inelastically in the labor market of the upazila. Consumer preferences incorporate a structure that combines Cobb-Douglas consumption of agricultural and manufacturing goods, and CES aggregation over crops and varieties:

$$U_u = C_{u,A}^{\alpha} C_{u,M}^{1-\alpha}$$

$$\text{where} \quad C_{u,M} = \left[\sum_n c_{un,M}^{\frac{\sigma_m - 1}{\sigma_m}} \right]^{\frac{\sigma_m}{\sigma_m - 1}}, \quad C_{u,A} = \left[\sum_c (a_c)^{\frac{1}{\sigma_a}} C_{u,c}^{\frac{\sigma_a - 1}{\sigma_a}} \right]^{\frac{\sigma_a}{\sigma_a - 1}}$$

$$\text{and} \quad C_{u,c} = \left[\sum_n c_{un,c}^{\frac{\sigma_c - 1}{\sigma_c}} \right]^{\frac{\sigma_c}{\sigma_c - 1}}$$

The upper nest is composed of Cobb-Douglas preferences over agricultural consumption $C_{u,A}$ and manufacturing consumption $C_{u,M}$. α represents the share of expenditure that is allocated to agricultural goods. For each crop $c \in C$ and the manufacturing good, consumption $C_{u,c}$ and $C_{u,M}$ are aggregated over varieties of the good from all other upazilas. $\sigma_m > 1$ determines how substitutable manufacturing varieties are with each other, $\sigma_a > 1$ determines substitutability across crops $c \in C$, and $\sigma_c > 1$ determines how substitutable are different varieties of each crop c. a_c represents CES weights, with $\sum_c a_c = 1$.

Solving the representative consumer's utility maximization problem delivers the associated expenditure in upazila u on each crop variety and manufacturing good variety:

$$\begin{aligned} \text{Manufacturing:} \quad x_{M,un} &= \left(\frac{p_{un,M}}{P_{u,M}}\right)^{1-\sigma_m} (1-\alpha) Y_u \\ \text{Crops:} \quad x_{c,un} &= \left(\frac{p_{un,c}}{P_{u,c}}\right)^{1-\sigma_c} \left(\frac{P_{u,c}}{P_{u,A}}\right)^{1-\sigma_a} a_c \alpha Y_u \quad \forall c \end{aligned} \tag{2.3}$$

where $x_{M,un}$ is total expenditure on the manufacturing good variety from upazila n in upazila u, $x_{c,un}$ is total expenditure on the crop c variety from upazila n in upazila u, Y_u is total income in upazila u, and $p_{un,c}$ is the price of crop c produced by region n and sold in u. This price depends on the iceberg trade cost and the price at source upazila $p_{un,c} = \tau_{un} p_{n,c}$. The associated price indices are given below:

$$\begin{aligned} P_u &= P_{u,M}^{1-\alpha} P_{u,A}^{\alpha} \\ P_{u,M}^{1-\sigma_m} &= \sum_n (p_{un,M})^{1-\sigma_m} \\ P_{u,A}^{1-\sigma_a} &= \sum_{c \in C} a_c (P_{u,c})^{1-\sigma_a} \\ P_{u,c}^{1-\sigma_c} &= \sum_n (p_{un,c})^{1-\sigma_c} \quad \forall c \end{aligned}$$

$P_{u,c}$ is the price index for crop c in upazila u and is an aggregate over prices of all varieties. $P_{u,A}$ is the agriculture price index and is an aggregate over the price index of different crops. $P_{u,M}$ is the price index of the manufacturing sector in upazila u, and P_u is the overall price index, which is a Cobb-Douglas aggregate of the manufacturing and agriculture price indices.

2.4.2 Production

Land in each region is divided into a continuum of plots of equal size. There are immobile landlords who own the land and earn income from land rents. Production of each crop requires a combination of land and labor, with share of each determined by crop specific γ_c.

For each plot i in upazila u, the total return from growing crop c is given by

$$p_{u,c} \mu_{u,c} (A_{i,u,c} K_{i,u})^{\gamma_c} l_{i,u,c}^{1-\gamma_c} \tag{2.4}$$

$A_{i,u,c}$ represents crop-specific draw of agricultural productivity, which is independently and identically Fréchet distributed across plots: $F_{u,c}(a) = \Pr[A_{i,u,c} \leq a] = e^{-\left(\frac{A_{u,c}}{a}\right)^{\theta}}$. The productivity draw depends on an upazila-crop specific scale parameter $A_{u,c}$, which captures the productivity of crop c in upazila u. $\theta > 1$ is the shape parameter, which is an inverse measure of heterogeneity of productivity draws across plots. The total return of each crop depends on the price of the crop $p_{u,c}$, the climate shock associated with crop c in u, $\mu_{u,c}$, the idiosyncratic productivity draw $A_{i,u,c}$,

and total land and labor input. I interpret climate shocks $\mu_{u,c}$ as capturing long-term shifts in the expectation of agents about future damage from climate shocks on productivity, which agents take as given at the time of cropping decisions.[15] $\mu_{u,c} \in [0,1]$, and the higher the flooding and cyclone propensity, the lower the value of $\mu_{u,c}$, with the relationship captured by a damage function that will be calibrated later. For tractability, I abstract from the case where the realization of the shock $\mu_{u,c}$ is different from the expectation of the shock.[16] An implication of no uncertainty is that farmers take prices of each crop as given at the time of their cropping decisions.

There is no market for land as land is owned by immobile landlords, but labor is hired in the labor market of upazila u at upazila-specific wage w_u.

The FOC for labor is given by

$$(1-\gamma_c)p_{u,c}\mu_{u,c}(A_{i,u,c}K_{i,u})^{\gamma_c}l_{i,u,c}^{-\gamma_c} = w_u \tag{2.5}$$

Combining equation 2.4 and equation 2.5 and using the fact that revenue net of labor costs accrue to the farmer as rents, the rental return per unit of land from using the plot i for growing crop c is given by

$$r_{i,u,c} = A_{i,u,c}\gamma_c(\mu_{u,c}p_{u,c})^{\frac{1}{\gamma_c}}\left(\frac{1-\gamma_c}{w_u}\right)^{\frac{1-\gamma_c}{\gamma_c}} \tag{2.6}$$

The landlord compares the return in equation 2.6 across crops and plants the one that offers the highest rent. They solve for the following maximization problem:

$$\text{Max}_c\ r_{i,u,c} \tag{2.7}$$

There is also a manufacturing sector which is linear in labor and assumed to be unaffected by climate shocks.[17] $A_{u,M}$ is the productivity of upazila u in the manufacturing sector. The FOC of the manufacturing sector pins down the wage rate, and is assumed to be unaffected by the climate shocks.

$$p_{u,M}A_{u,M} = w_u \tag{2.8}$$

[15] Table B.12 shows that agents' decisions on crops are influenced not just by flooding and cyclone shocks in recent years, but also by shocks further in the past, even after controlling for more recent shocks.

[16] See Allen and Arkolakis [2014] for a paper that studies the case where productivity is volatile and farmer preferences are risk averse.

[17] I assume that the non-agricultural sector is unaffected by climate shocks based on the results in table 2.2, and the findings in Colmer [2021] and Albert et al. [2021] that the share of agricultural employment declines in the face of higher temperatures and droughts respectively. This assumption relates to the relative impact of climate shocks on the agriculture and non-agriculture sectors and does not necessarily imply no absolute effect on the latter.

2.4.3 Crop choice

Solving the maximization problem in equation 2.7 using the Fréchet assumption, the land share in each upazila u dedicated to growing crop c is given by:

$$\begin{aligned} \pi_{u,c} &= \frac{\left(A_{u,c}\beta_{u,c}\right)^{\theta}}{\Phi_u^{\theta}} \\ \text{where} \quad \Phi_u &= \left[\sum_k \left(A_{u,k}\beta_{u,k}\right)^{\theta}\right]^{1/\theta} \end{aligned} \tag{2.9}$$

The share of land devoted in upazila u to crop c, $\pi_{u,c}$, will depend on the innate productivity of the upazila $A_{u,c}$ and $\beta_{u,c}$, which like in Sotelo [2020] can be interpreted as the return per unit of efficiency land, as equation 2.6 implies $r_{i,u,c} = A_{i,u,c}\beta_{u,c}$.[18] Given a set of prices and wages, an increase in upazila-crop level productivity $A_{u,c}$ will lead to a higher share of land being used for that crop. Similarly, an increase in flooding or cyclone propensity for crop c will decrease $\mu_{u,c}$, leading to a decline in share of land used for the crop.[19] Φ_u is an upazila-specific summary statistic that summarizes the effect of prices, productivity, and climate shocks of all other crops on the share of land used for crop c.

Crop c will be grown only on those plots where it offers the highest returns. The distribution of productivities of plots that actually grow crop c will be given by the conditional distribution $\Pr[A_{i,u,c} \leq a \mid A_{u,c}\beta_{u,c} > A_{u,k}\beta_{u,k}\ \forall k \neq c]$, which using the properties of the Fréchet distribution can be calculated as[20]

$$G_{u,c}(a) = \exp\Big\{ -\frac{\Phi_u^{\theta}}{\left(\beta_{u,c}a\right)^{\theta}} \Big\} \quad \forall c \tag{2.10}$$

2.4.4 Sectoral employment

Labor demand per unit of land can be derived from equation 2.5 and will be given by

$$l_{i,u,c} = \left(\frac{1-\gamma_c}{w_u}\right)^{1/\gamma_c} A_{i,u,c}(p_{u,c}\mu_{u,c})^{1/\gamma_c} \tag{2.11}$$

[18] $\beta_{u,c} = \gamma_c(\mu_{u,c}p_{u,c})^{\frac{1}{\gamma_c}} \left(\frac{1-\gamma_c}{w_u}\right)^{\frac{1-\gamma_c}{\gamma_c}}$

[19] Note that land shares for crop c will also respond to increases in flooding and cyclone propensity for crops other than c in upazila u, an idea captured by columns 3 and 4 of table 2.1. An increase in flooding or cyclone propensity for crop $c' \neq c$ will lead to a larger land share being devoted to crop c.

[20] the associated PDF of equation 2.10 is

$$\frac{\theta\Phi_u^{\theta}a^{-\theta-1}}{(\beta_{u,c})^{\theta}} \times \exp\left\{-\frac{\Phi_u^{\theta}}{(\beta_{u,c}a)^{\theta}}\right\} = g_{u,c}(a) \quad \forall c$$

Note that equation 2.11 gives labor demand only if that particular plot is used to grow crop c. The actual labor demand to grow crop c in upazila u will be given by summing labor demand across all plots that actually grow crop c, for which the conditional distribution from equation 2.10 needs to be used[21]:

$$\begin{aligned} l_{u,c} &= \pi_{u,c} K_u \int_{i \in \{r_{iuc} > r_{iuk} \ \forall k\}} \left(\frac{1-\gamma_c}{w_u}\right)^{1/\gamma_c} A_{i,u,c} (p_{u,c}\mu_{u,c})^{1/\gamma_c} \\ &= \pi_{u,c} K_u \times \left(\frac{1-\gamma_c}{w_u}\right) \frac{\Phi_u}{\gamma_c} \Gamma\left(1 - \frac{1}{\theta}\right) \end{aligned} \tag{2.12}$$

Total labor used in growing crop c in upazila u, $l_{u,c}$, thus depends on the land used for growing crop c in upazila u, $\pi_{u,c}K_u$, the summary statistic Φ_u, and wage w_u. $\Gamma\left(1-\frac{1}{\theta}\right)$ is the Gamma function. Total labor used to grow crop c increases with the total land used for crop c and with the summary statistic Φ_u but decreases with the wage rate w_u. Total demand for labor in agriculture in upazila u, $l_{u,A}$, is the sum of labor demand across all crops and can be calculated as follows:[22]

$$l_{u,A} = \sum_c l_{uc} = K_u \frac{\Phi_u}{w_u} \Gamma(1 - \frac{1}{\theta}) \sum_c \pi_{u,c} \times \left(\frac{1-\gamma_c}{\gamma_c}\right)$$

2.4.5 Total land rents

Based on equation 2.6, total rents for all plots that grow crop c depend on the land used to grow crop c, and the average return in those plots that actually decide to grow crop c in upazila u. Total rents will be given by

$$\begin{aligned} r_{u,c} &= \pi_{u,c} K_u \int_{i \in \{r_{iuc} > r_{iuk} \ \forall k\}} A_{iuc}\, \gamma_c (\mu_{u,c} p_{u,c})^{\frac{1}{\gamma_c}} \left(\frac{1-\gamma_c}{w_u}\right)^{\frac{1-\gamma_c}{\gamma_c}} \\ &= \pi_{u,c} K_u \times \beta_{u,c} \int_0^\infty a\, g_{u,c}(a)\, da \\ &= \pi_{u,c} K_u \Phi_u \Gamma\left(1 - \frac{1}{\theta}\right) \end{aligned}$$

Total return from land is simply given by $K_u \Phi_u \Gamma(1 - \frac{1}{\theta})$, which is sum of total rents across all crops. Total rents in an upazila thus depends on land K_u and the summary statistic Φ_u.[23]

[21] It is useful to remember the mean of the conditional distribution in order to derive this: $\int_0^\infty a g_{uc}(a) da = \frac{\Phi_u}{\beta_{uc}} \times \Gamma(1 - \frac{1}{\theta})$

[22] Note that when the labor and land shares are equal across crops, such that $\gamma_c = \gamma$, total labor demand in agriculture will boil down to $K_u \frac{\Phi_u}{w_u} \Gamma\left(1 - \frac{1}{\theta}\right) \times \left(\frac{1-\gamma}{\gamma}\right)$.

[23] The $\Gamma(1-\frac{1}{\theta})$ shows up after taking the mean of productivities of plots in upazila u that actually grow crop, which are also Frechet distributed based on equation 2.10.

2.4.6 Market clearing

The total income of an upazila is the sum of labor income and income from land rents.

$$Y_u = w_u L_u + K_u \Phi_u \Gamma (1 - \frac{1}{\theta})$$

For labor market clearing, we need the number of workers in agriculture and manufacturing to equal the total population of the upazila:

$$\sum_c l_{u,c} + l_{u,M} = L_u \tag{2.13}$$

where l_{uM} in equation 2.13 represents the labor demand for the manufacturing sector. For market clearing of the final goods, we need the labor and rental income from selling each variety to equal the expenditure on each good by all upazilas. The market clearing equations will be:

$$\begin{aligned} \text{Manufacturing:} \quad & w_u l_{u,M} = \sum_n x_{M,nu} \\ \text{Crops:} \quad & w_u l_{u,c} + r_{u,c} = \sum_n x_{c,nu} \quad \forall c \end{aligned} \tag{2.14}$$

2.4.7 Equilibrium

Given exogenous variables land K_u, labor L_u, productivities $\{A_{u,c}, A_{u,M}\}_{\forall u,c}$, climate shocks $\{\mu_{u,c}\}_{\forall u,c}$, trade costs $\{\tau_{um}\}_{\forall u,m}$ and parameters $\{\alpha, \sigma_c, \sigma_m, \sigma_a, a_c, \theta, \gamma_c\}$, an equilibrium is a set of crop prices $\{p_{u,c}\}_{\forall u,c}$, manufacturing goods prices $\{p_{u,M}\}_{\forall u}$, and wages $\{w_u\}_{\forall u}$, such that (i) given prices and wages, consumers maximize utility according to equation 2.3 (ii) given prices and wages, land and labor in each upazila is allocated to its most efficient use, according to equation 2.9 and 2.12, and (iii) labor and product markets clear according to equations 2.13 and 2.14. Section B.4.1 in the appendix extends the model above to allow for migration.

2.5 Taking the model to the data

In this section, I describe the parameterization of the model introduced in section 2.4. The model will have $N = 451$, representing the upazila boundaries of 1981, and $C = 6$ crops, representing Aus rice, Aman rice, Boro rice, Wheat, Jute and Potato. Table 2.3 provides a summary of calibrated/estimated parameters.

I draw demand side elasticities in the model from the literature. Following Caliendo and Parro [2015], the elasticity of substitution across varieties within a crop, σ_c, is set at 9.5 for all crops and the elasticity of substitution across varieties of the manufacturing good, σ_m, is set at 5.5. For the

Table 2.3: Summary of calibration/estimation of parameters

Parameters	**Source/method for calibration**
α (0.6)	Share of expenditure on food in HIES 2010
σ_m (5.5), σ_c (9.5)	Caliendo and Parro [2015]
σ_a (2.5)	Sotelo [2020], Farrokhi and Pellegrina [2023]
θ (3)	Sotelo [2020], Bergquist et al. [2022]
$\{a_c\}_{\forall c}$	Calibrated to match the expenditure on each crop in HIES 2010
$\{A_{um}\}_{\forall u}$	Calibrated to match share of upazila-level manufacturing employment in total manufacturing employment in 2011
$\{\mu_{uc}\}_{\forall u,c}$	Indirect inference with logistic or exponential functional form
γ_c	Calibrated using indirect inference
$\{\tau_{un}\}_{\forall u,n}$	Fast Marching method using 2011 road network map
	+ estimates from Pellegrina [2022]
$\{A_{uc}\}_{\forall u,c}$	Upazila crop-specific estimates of productivity by BARC
$\{L_u\}_{\forall u}$	Total employment in each upazila in 2011

elasticity of substitution across crops, I set $\sigma_a = 2.5$ following Sotelo [2020]. This is also in line with Farrokhi and Pellegrina [2023], who estimate an elasticity of 3.1. I set $\alpha = 0.6$, which is the share of total income spent on agriculture, based on the share of consumption expenditure on food in Bangladesh's HIES (Household Income and Expenditure Survey) 2010.

For upazila-crop specific productivities $\{A_{u,c}\}_{\forall u,c}$, I use surveys by BARC (Bangladesh Agricultural Research Council), who rate the suitability of each upazila for each of the major crops based on 11 different parameters, such as soil permeability, soil salinity, soil nutrients, etc.[24] The data can be thought of as similar to GAEZ data used in Costinot et al. [2016], but available at the level of upazilas and for the six major crops that are the focus of this paper. Figure B.6 in the appendix shows the relationship between calibrated productivities and land shares for Aman rice and Wheat using a binned scatterplot. As can be seen in the figure, there is a positive relationship between the productivity of the crop and the share of land (net cultivated area) devoted to the crop.[25] θ, which captures the variance of productivity draws across plots within an upazila, is set at 3. While Sotelo [2020] estimates a value of 1.7, Berger et al. [2022] estimate a value between 1.8 and 4. For robustness, I also use $\theta = 2$ and $\theta = 4$ in calculating the value of adaptation in Section 2.6. Finally, because there is no unemployment in the model, I take total employment in each upazila in 2011 as a measure of the population of the upazila, L_u.

The climate shocks in the model, $\mu_{u,c}$, are numbers between 0 and 1, with 1 representing the case where there are no climate shocks. In the data, however, I observe not the realizations of $\mu_{u,c}$ but realizations of flooding (in meters) and cyclones (in kmph). Thus, a damage function is needed to map realizations of climate shocks in the data to $\mu_{u,c}$. I assume that the $\mu_{u,c}$ shock in the model at any given point in time t is multiplicative in the damage functions of cyclone and flooding shocks:

$$\mu_{uc,t} = \mu_f(f_{uc,t}) \times \mu_c(c_{uc,t})$$

Where $\mu_f(f_{u,c,t})$ represents the flooding damage function and $\mu_c(c_{u,c,t})$ represents the cyclone damage function. In line with the definition of flooding and cyclone shocks in Section 2.3, $f_{u,c,t}$ and $c_{u,c,t}$ capture medium-term averages of flooding and cyclone incidence, while $\mu_{u,c,t}$ captures perceived damage to crop c given those averages. Both these functions are $\mu : \mathbb{R}^+ \to [0, 1]$. The climate literature has long discussed damage or hazard functions in the context of climate shocks (see Prahl et al. [2016] for a review in the climate literature and Nordhaus and Moffat [2017] for a survey in environmental economics). I work with two parameterizations of the damage functions. The baseline parameterization assumes a logistical form for the damage function.

[24] The data can be found here.

[25] The data from Agriculture Census 2008 were used to calculate land shares for Aman rice and Wheat in Figure B.6.

$$\mu_{uc,t} = \frac{1}{1+\zeta_{fl} f_{uc,t}^2} \times \frac{1}{1+\zeta_{cyc} c_{uc,t}^2} \tag{2.15}$$

In the damage function in equation 2.15, the parameters ζ_{fl} and ζ_{cyc} regulate the extent to which increases in flooding and cyclone propensity translate into perceived damage. Note that they do not vary by crop, but different crops in an upazila can still have different $\mu_{u,c}$ based on different average flooding and cyclone incidence during the crop's season. When both flooding and cyclone propensity are 0, $\mu_{u,c,t} = 1$ and there is no damage to output. I also work with an alternative parameterization that assumes an exponential form for the damage function.[26]

The climate parameters ζ_{fl} and ζ_{cyc}, along with the rest of the parameters such as the land share in production γ_c, crop-specific CES weights $\{a_c\}$, and manufacturing sector productivities $\{A_{u,M}\}$, are calibrated internally. I calibrate a single value for γ_c, γ, which does not vary by crop. The calibration is done using two loops. In the inner loop, for a given value of ζ_{fl}, ζ_{cyc}, and γ, $\{a_c\}$ are calibrated such that the share of expenditure on each of the six crops in the model matches the expenditure share in the data.[27] $\{A_{u,M}\}$ is calibrated to match the share of upazila-level manufacturing employment in total manufacturing employment in the model to the corresponding share in the 2011 data. The outer loop calibrates ζ_{fl}, ζ_{cyc}, and γ via indirect inference, such that the distance between regression coefficients using simulated data matches the coefficients in Section 2.3.[28] Parameters ζ_{fl} and ζ_{cyc} regulate the extent to which increases in flooding or cyclone propensity translate into damage and influence the extent to which crop choice responds to increases in climate risk based on equation 2.9. They thus influence the counterparts of $\beta_{fl,crop}$ and $\beta_{cyc,crop}$ in equation 2.1 in the model-simulated data. γ directly affects the extent to which increases in flooding and cyclone propensity lead to the shifting of workers from agriculture into manufacturing. A higher labor share, or a lower γ, would imply a bigger shift of workers from agriculture to non-agriculture sectors. γ directly influences the counterparts of $\beta_{fl,emp}$ and $\beta_{cyc,emp}$ in equation 2.2 in the model-simulated data.

I perform the calibration using a grid search over different combinations of ζ_{fl}, ζ_{cyc}, and γ. The calibrated value for the share of land in the agricultural production function is $\gamma = 0.4$.[29] The

[26] Under the exponential parameterization, the damage function is $\mu_{u,c,t} = \exp(-\zeta_{fl} f_{u,c,t}) \times \exp(-\zeta_{cyc} c_{u,c,t})$.

[27] Isolating the expenditure on rice, wheat, jute, and potato in HIES 2020, rice accounted for 71.25% of expenditure, wheat 12.1%, jute 10.4%, and potato 6.25%. The 71.25% share is apportioned to each variety of rice based on the share of production of each variety in the 2008 Agricultural Census. This leads to the Aus share being 9.25%, the Aman share being 33.5%, and the Boro share being 28.5%.

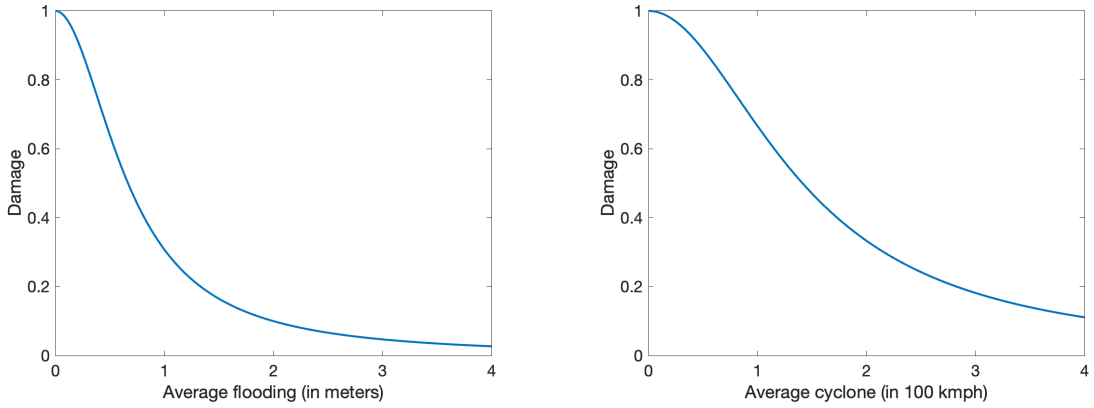
[28] I generate simulated data by solving the model using two sets of climate shocks: the average flooding and cyclone incidence at the upazila-crop level in 2000–2010 versus the worst flood and cyclone shock in the 1960–2010 period. The outcome and climate variables are then differenced and a regression similar to Table B.4 and Table B.8 is run. ζ_{fl}, ζ_{cyc}, and γ are calibrated to match the regression coefficients in the model-generated data to the coefficients in column 1 of Tables B.4 and B.8. The coefficient on flooding in column 1 of Table B.8 is given zero weight, in effect reducing the number of data coefficients to three.

[29] Farrokhi and Pellegrina [2023] have a Cobb-Douglas technology in agriculture combining land and labor. They

calibrated values of the climate parameters are $\zeta_{fl} = 2.25$ and $\zeta_{cyc} = 0.5$. The calibrated damage functions for flooding and cyclones are displayed in Figure 2.1. Conditional on there being no cyclones in an upazila, an average flood propensity of 1 meter implies a $\mu_{u,c}$ of 0.31. Similarly, an upazila with no flooding but an average cyclone propensity of 100 kmph implies a $\mu_{u,c}$ of 0.67. To get a sense of what the calibration means in terms of $\mu_{u,c}$, Figure B.8 in the appendix plots the calibrated climate shocks based on average flooding and cyclone incidence between 2000 and 2010 for Aman rice and wheat. For both crops, a number of upazilas have limited impacts from climate shocks, with $\mu_{u,c}$ being close to 1 for most upazilas. A bigger share of upazilas have substantive climate shocks for Aman rice than for wheat, which is unsurprising given that the Aman season coincides with both flooding and cyclone seasons.

When working with the exponential parameterization, I replace the functions in equation 2.15 with $e^{-\zeta_{fl}}$ and $e^{-\zeta_{cyc}}$ and redo the calibration outlined above.[30] The calibrated damage functions under the exponential parameterization are shown in Appendix Figure B.7.

Figure 2.1: Calibrated damage functions (logistic parameterization)



(a) Flooding (b) Cyclones

Finally, I parameterize the transport costs by applying the Fast Marching Method (FMM) on a road network map of Bangladesh. FMM allows calculating the travel times between any two upazilas of Bangladesh. To convert travel times into trade costs, I use the functional form in Pellegrina [2022]. Section B.1.3 in the appendix explains the steps taken for the FMM procedure and to calculate trade costs in more detail.[31]

estimate a labor share of 0.45, and thus a land share of 0.55, for traditional production technology.

[30]With the exponential parameterization, $\zeta_{fl} = 1.5$, $\zeta_{cyc} = 0.5$, and $\gamma_c = 0.5$. Note that the calibration with the exponential parameterization also results in different calibrated values for CES weights $\{a_c\}$ and manufacturing productivities $\{A_{u,M}\}$ compared to the logistic parameterization.

[31]Note that I am unable to back out trade costs from trade flows due to lack of within country trade data.

2.6 Baseline equilibrium and value of adaptation

I solve the baseline equilibrium with the model parameterized in Section 2.5, but using the average climate shocks from 2001 to 2010. The model delivers equilibrium prices $\{p_{u,c}\}_{\forall u,c}$ and $\{p_{u,M}\}_{\forall u}$, which can be used to construct the objects of focus in Section [sec:Empirical-results]: land shares for each crop in each upazila $\{\pi_{u,c}\}_{\forall u,c}$ and the number/share of workers in agriculture in each upazila $\{l_{u,A}\}_{\forall u}$. In the model extension in Section B.4.1, where migration is allowed, the total population in each location, $\{L_u\}_{\forall u}$, is also determined in equilibrium.

2.6.1 Calculating the value of adaptation

To calculate the *value of adaptation*, I introduce alternative upazila-crop level climate shocks of different intensities and correlatedness. Specifically, the three intensities are 1.5, 2, and 2.5 times the average flooding and cyclone incidence during the 2001 to 2010 period. The correlatedness varies from correlated (such that all upazila-crop combinations have the same intensity), correlated at the upazila level (such that all crops within an upazila receive the same intensity, but can vary across upazilas) to uncorrelated (such that all upazila-crop combinations receive different intensities).[32] This leads to 9 unique sets of climate shocks. Note that a doubling of cyclone and flooding propensity does not imply a double of climate shock $\mu_{u,c}$: the calibrated damage functions in figure 2.1 regulate the extent to which flooding and cyclone propensity translate into damage to agricultural output.

For each set of alternative shocks, I solve two versions of the model. In the first version, the economy is allowed to adjust freely. In the second version, labor $\{l_{uc}, l_{uM}\}_{\forall u,c}$ and land use $\{\pi_{uc}\}_{\forall u,c}$ is fixed as in the baseline equilibrium and no adaptation is allowed. Section B.4.2 in the appendix provides the additional equations necessary to solve the no adaptation version of the model.[33] For each of the nine combinations of alternative climate shocks, a unique value of adaptation is defined based on how much worse welfare impact of counterfactual climate shock is in the model without adaptation, versus model with adaptation.[34] I define welfare to be sum of real income across upazilas $\sum_u \frac{Y_u}{P_u}$.

Table 2.4 shows the value of adaptation for alternative sets of climate shocks discussed above. When the counterfactual shock is $2\times$ 2000's average flooding and cyclone incidence, the welfare is 3.85% lower in the model without adaptation but only 2.98% lower with adaptation, implying

[32] When working with uncorrelated shocks, I vary the intensity across upazilas and/or crops, but maintain the average same average intensity as the correlated shocks case.

[33] This method of estimating the importance of adaptation by fixing outcomes as in the baseline equilibrium but using counterfactual climate shocks aligns with the method in Rudik et al. [2022].

[34] For example, if welfare in the baseline equilibrium is 100, 95 in the model with adaptation and 93 in the model without adaptation, the value of adaptation is calculated as $\left(\frac{W_{V2}-W_{V1}}{W_{V1}-W_{bs}}\right) \times 100 = \frac{-2}{-5} \times 100 = 40\%$.

a value of adaptation of 29.2%. This means the welfare impact of increase in climate risk is 29.2% worse in a world without adaptation, relative to a world with adaptation. Another way of representing this is to say that adaptation offsets the impact of increasing climate risk by roughly 23%.

The value of adaptation increases with the intensity of the future shocks but decreases with their correlatedness. Allowing for no adjustment is costlier when the change in climate shock with respect to the baseline shocks is higher, as the economy will be further from the optimal allocation of land and labor. Correlated shocks imply lower adaptation value as there are fewer options to adjust to. If Aman and Aus rice are both seeing a shock of similar magnitude, there is little value in adapting away from one to the other. This intuition can be seen in equation 2.9: abstracting away from price changes, an increase in $\{\mu_{uc}\}$ in equation 2.9 is proportionally the same for all crops will not change land shares.[35]

Table 2.4: Value of adaptation

	Intensity of the shock		
	$1.5\times$ 2000's avg	$2\times$ 2000's avg	$2.5\times$ 2000's avg
Uncorrelated shocks	23.6%	37.7%	47%
Correlated at upazila level	20.2%	32.1%	39.9%
Correlated shocks	16.9%	29.3%	38.2%

In the model extension where migration is allowed, the baseline equilibrium involves solving not just for prices $\{p_{u,c}\}_{\forall u,c}$ and $\{p_{u,M}\}_{\forall u}$, but also for the labor allocation $\{L_u\}_{\forall u}$ deciding to live in each upazila. When calculating the value of adaptation in a model where migration is allowed, the version of the model without adaptation includes fixing not just labor and land use, but also fixing the number of workers that live in each location.[36] The chosen value of migration elasticity is 2. In developing-country contexts, Morten and Oliveira [2024] estimate an elasticity of migration to real wages in Brazil of 1.9, while Tombe and Zhu [2019] estimate a value of 1.2 to 1.6 in the context of China. Table 2.5 shows the value of adaptation in a model where migration is allowed. In general, the value of adaptation rises by 10 to 12 percentage points if migration is allowed in the model. The value of adaptation now captures the adjustment margin of not just land use and

[35]Of course, the same proportionate increase in flooding or cyclone shocks will still change land shares due to non-linearity of the damage function.

[36]To keep numbers comparable to the model without migration, the object of welfare in the model where migration is allowed is still defined based on $\sum_u \frac{Y_u}{P_u}$, instead of the object that is equalized across locations given in equation B.2. This also helps compare the numbers to the version of the model with migration where no adaptation is allowed, as the object in equation B.2 is no longer equalized.

labor allocation across sectors and crops within an upazila, but also the allocation of labor across upazilas.

Table 2.5: Value of adaptation with migration

	Intensity of the shock		
	$1.5\times$ 2000's avg	$2\times$ 2000's avg	$2.5\times$ 2000's avg
Uncorrelated shocks	34.3%	48.8%	58.3%
Correlated at upazila level	31%	43.6%	51.7%
Correlated shocks	28.1%	41.1%	50.2%

The numbers in table 2.4 and 2.5 are in line with what earlier work has calculated, even though the nature of climate shocks, the adjustment margins, counterfactual increases in climate risk and modeling choices vary across papers. Using a dynamic model, Rudik et al. [2022] find that migration and sectoral reallocation mitigates one-fourth of the negative effects of climate change on welfare in the US. Focusing on temperature-driven reductions in demand for agricultural labor in India, Colmer [2021] estimates that in the absence of labor reallocation from agriculture to non-agriculture sector, local economic losses would be 49 percent higher. The value of adaptation in table 2.4, which focuses only on crop changes and sectoral reallocation, is lower than the estimate in Costinot et al. [2016]. They find that global welfare losses from climate change are 0.26% of GDP, but 0.78% of GDP i.e. 3 times larger, when farmers cannot reallocate production across crops.[37]

2.6.2 Robustness checks to the value of adaptation

I test the robustness of the results in Table 2.4 and 2.5. Table B.13 shows the value of adaptation if the assumed functional form is exponential and Table B.14 shows the value of adaptation if the functional form is exponential and migration is allowed. The value of adaptation is similar across the two functions, albeit a bit lower with the exponential functional form. In the baseline equilibrium, $\theta = 3$. Table B.15 and Table B.16 show the value of adaptation when $\theta = 2$ and $\theta = 4$ respectively. In general, a higher θ implies a larger value of adaptation because crop choice responds more to increases in flooding and cyclone shocks, as can be seen in equation 2.9. The importance of adaptation increases with θ as the gap between the frictionless equilibrium and the no adaptation equilibrium increases.

[37]This is partly a function of how value of adaptation is defined. The absolute difference between adaptation and no adaptation welfare, relative to baseline welfare, is comparable with Costinot et al. [2016]: 0.87% of baseline welfare here versus 0.52% of baseline GDP in Costinot et al. [2016].

There is one drawback with the counterfactual shocks introduced in Tables 2.4 and 2.5: flooding and cyclone propensity is worsened under the alternative shocks only in upazilas that had non-zero propensity of the shocks in the 2001–2010 period, i.e., worsening happens along an intensive margin. For any upazila with zero average flooding in the 2000s, the alternative shocks also have zero average flooding. To address this, I calculate value of adaptation under a 'worst case' scenario, where the alternative climate shocks are the worst realization of the shock that the upazila-crop combination saw between 1960 and 2010. I find that the value of adaptation under the worst case scenario is 23.7%.[38]

2.6.3 Spatial heterogeneity in the value of adaptation

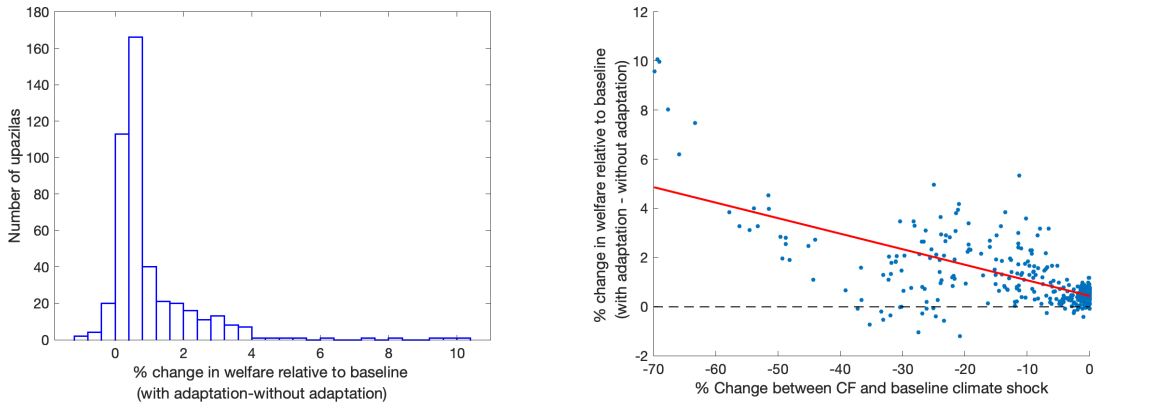
Upazilas do not gain equally from adaptation. To explore the extent to which value of adaptation varies across upazilas, I focus on the counterfactual where flooding and cyclone intensity at the upazila-crop level is $2\times$ it's 2000's average, and such increases are perfectly correlated across upazilas and crops. This counterfactual is the third row and middle column in table 2.4.

Figure 2.2 plots the upazila level difference in welfare in the world with adaptation and without adaptation, in response to counterfactual increases in flooding and cyclone propensity. For Bangladesh as a whole, welfare is 3.85% lower in the model without adaptation but only 2.98% lower with adaptation, relative to baseline equilibrium, implying a difference of 0.87%. However, this number hides substantial heterogeneity across upazilas. As can be seen in panel a of figure 2.2, most upazilas (95%) gain from adaptation, with roughly 5% of upazilas being worse off in the world without adaptation.

What determines whether an upazila is better off with or without adaptation? The key factor is the intensity of the counterfactual climate shock. Panel b of figure 2.2 plots the difference in welfare in the model with adaptation and the model without adaptation, relative to the baseline equilibrium, against the average percentage change in $\mu_{u,c}$ for each upazila. In general, the larger the decreases in average μ_{uc} due to increasing flooding and cyclone propensity, the more valuable is adaptation for the upazila.

[38] Under this scenario, welfare would be 9.95% lower without adaptation, but 8.05% lower with adaptation.

Figure 2.2: Heterogeneity in gains from adaptation in response to increase in climate shocks



(a) Distribution of welfare

(b) Welfare gain vs increase in climate shock

2.7 Conclusion

I study the importance of adaptation in dealing with an increase in climate risk. Using long-term data on flooding and cyclones in Bangladesh from 1960 to 2010, I find that an increase in propensity of flooding and cyclones during a crop's season shifts regions out of those crops. However, while increase in cyclone propensity shifts workers out of agriculture into the non-agriculture sector, increase in flooding does not.

I then develop a structural model that incorporates these two channels of adaptation and calculate the value of adaptation i.e. in the face of increasing climate risk, how much worse would welfare be if the two adaptation channels were shut off. The parameters of the model are disciplined by the adaptation responses in the empirical section. I find that when intensity of both flooding and cyclones doubles relative to the 2000s average, the value of adaptation is 29.2%. In an extended model that allows for migration, the value of adaptation goes up to 41.1%. The value of adaptation increases with the intensity of future shocks but decreases with their correlatedness across crops and regions.

The paper highlights that agents adapt in various ways when facing increase in climate risk, and such adaptation partly offsets the negative effects on welfare. A useful extension of the paper could be to think meaningfully about uncertainty of future climate shocks, something I abstract from in this paper. Another extension could be to work on instruments for adaptation. For example, what interventions can the governments make to ease transition of farmers from high to low climate risk crops, or interventions to move them out of agriculture and riskier regions? Identifying the design and nature of such interventions and evaluating their efficacy could be a useful next step.

CHAPTER 3

How Critical are Critical Minerals? Firm-level Evidence from the 2010 China's Rare Earth Export Restriction

Abstract

We study how US firms adapted to the 2010 China's rare earth export restriction, using confidential firm-trade linked microdata, comparing rare earth importers with those of other critical minerals that exhibit similarly high market concentration and technological importance. Despite only temporary supply disruptions, rare earth importers suffered persistent declines in employment and product mixes upto 8 years, even after price reverted to pre-shock levels in 2015. These findings are difficult to be reconciled with standard trade models. They highlight the role of shifted expectations about future policy and the complex interdependencies within firms' production processes.

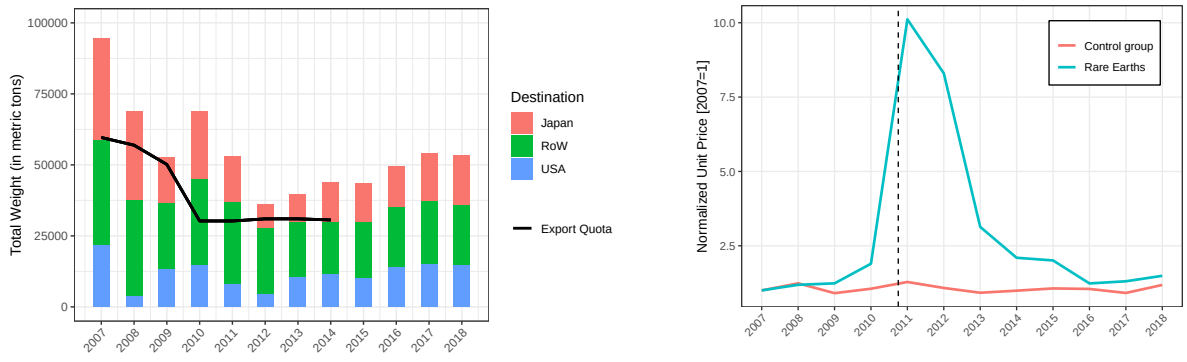
3.1 Introduction

Amid escalating geopolitical tensions, China imposed export restrictions on rare earths on April 4, 2025, for the first time against the US in retaliation for the US's imposition of 125% tariffs. Even before this action, US policymakers had expressed growing concerns because rare earths are key inputs for defense and high-tech industries and China controlled roughly 60% of global mining and 90% of refining capacity as of 2023, making alternative supply sources hard to secure. Despite these concerns, micro-level evidence on how US firms respond to this restriction remains limited.

In this paper, we ask: how do US importers adjust to foreign export restrictions on rare earths, a critical mineral dominated by statecraft? We provide the first causal empirical evidence on this question using confidential firm-trade linked microdata that cover the almost entire universe of US firms and their trade transactions. We use China's 2010 rare earth export restriction as a natural experiment. Because it was imposed in response to a territorial dispute over the Senkaku/Diaoyu Islands, it is unlikely to be related to US-specific factors. The restriction led to global supply

shortfalls and sharp price increases until China lifted it in 2015 following a World Trade Organization (WTO) ruling (Panel (a) of Figure 3.1). Beyond these immediate effects, the 2010 episode altered firms' or policymakers' expectations by showing that China could use export controls as a geopolitical tool, thereby heightening uncertainty over rare earth supply chains.[1]

Figure 3.1: 2010 China's Rare Earth Export Restriction as a Natural Experiment



(a) 2010 export restriction and quantities exported

(b) Prices of rare earths and control group critical minerals

Note: Panel (a) plots the export restrictions imposed by China and the quantities exported to the US, Japan, and the rest of the world. Panel (b) plots the average prices of rare earths and the control group critical minerals, including cobalt, nickel, graphite, copper, lithium, tungsten, and molybdenum.

We use a diff-in-diff event study design. The treatment group consists of US firms that imported rare earths at least once between 2007 and August 2010 (1 month before the restriction). The control group consists of US firms that imported any of 7 other critical minerals—Cobalt, Nickel, Graphite, Copper, Lithium, Tungsten, and Molybdenum—but never rare earths during the same time window. These control minerals were chosen based on reports from the US Department of the Interior (DOI) and International Energy Association (IEA), which identify critical minerals by supply chain risks (e.g., global market concentration) and their roles as key inputs to high-tech and energy-saving technologies (e.g., electric vehicles). While rare earth prices skyrocketed more than tenfold after the restriction, prices for the control minerals remained stable (Panel (b) of Figure 3.1).

We combine a firm-level panel by merging three confidential Census micro datasets: the Longitudinal Firm Trade Transactions Database (LFTTD), the Longitudinal Business Database (LBD), and the Census of Manufacturers (CMF). The resulting dataset covers each US firm's import and

[1]For example, House Representative Donald A. Manzullo expressed concern at a hearing in September 2011: *"…The Chinese action sent a clear and unmistakable message to Japan and the rest of the world: China is willing to use economic tools to achieve diplomatic goals.…For America's defense industry, a total reliance on China for rare earth represents a serious weakness for national security. China currently controls 97 percent of the world's rare earth production.…"* [US House Committee on Foreign Affairs, 2011].

export flows of goods, balance sheet variables, and product mixes. In particular, we exploit the LFTTD's granular product-level trade information (8-digit HS code level) to identify which firms import each critical mineral.

We present three main empirical findings. First, the restriction led only to short-lived declines in firms' probability of exporting and total export values while it was in effect (2011-2015). Second, rare-earth importers suffered persistent employment for up to eight years after the restriction, relative to the control group. Remarkably, employment continued falling through 2018, despite prices normalizing and China lifting its quotas in 2015 after the WTO ruling. Third, these persistent declines coincided with persistent reductions in product variety. We document long-lasting drops in the number of exported products (unique 8-digit HS codes in the LFTTD).

These results are unlikely to be explained by standard workhorse trade models e.g. Costinot and Rodríguez-Clare [2014]. These workhorse models cannot explain persistent declines in employment long after prices returned to pre-shock levels, because export restrictions operate only through price increases. This persistence points instead to shifts in US firms' expectations that China might again deploy export controls for geopolitical ends, prompting restructuring of production reflected in narrower product mixes.

Related Literature First, this paper contributes the growing literature on supply chain consequences of trade policies [e.g. Flaaen et al., 2020, Barattieri and Cacciatore, 2023, Cox, 2023, Antràs et al., 2024, Lake and Liu, 2024, Flaaen and Pierce, 2024, Blanchard et al., 2025, Flaaen et al., 2025, Handley et al., 2025] by providing the first micro-level evidence on how export restrictions on rare earths affect downstream US importers. While recent studies examine firms' input sourcing diversification under supply chain risks [e.g., Grossman et al., 2023, Blaum et al., 2024, Castro-Vincenzi et al., 2024], we show that US firms could not diversify their rare earth sources, likely reflecting China's near-monopoly. Instead, these firms adjusted their product mixes. Our findings highlight the importance of expectations about future policy [Alessandria et al., 2025] and uncertainty [Pierce and Schott, 2016, Handley and Limão, 2017] for understanding trade policy effects.

Second, this paper contributes to the literature on geopolitics and international trade. While recent theoretical work examines the link between economic ties and geopolitics [e.g. Martin et al., 2008, Fajgelbaum et al., 2020, Clayton et al., 2023, Becko and O'Connor, 2024, Kleinman et al., 2024], micro-level empirical evidence on how firms adjust to geopolitical shocks remains scarce.[2] The most closely related study is Alfaro et al. [2024], which analyzes the innovation consequences

[2]Recent studies have examined trade fragmentation Alfaro and Chor [2023], Freund et al. [2024], Bonadio et al. [2025], Gopinath et al. [2025]; geopolitical risks Flynn et al. [2025]; technology transfers Liu et al. [2024], Choi et al. [2025]; sanctions Morgan et al. [2023], Bachmann et al. [2024], Becko [2024], de Souza et al. [2024]; and pandemic-driven trade disruptions Bown et al. [2022], Leibovici and Santacreu [2023], Traiberman and Rotemberg [2023].

of the 2010 export restriction. We use the same natural experiment but differ in two key aspects. First, we show that changes in firms' product mixes served as an important adaptation margin, showing the interdependencies within firms' production process, as studied by Ding et al. [2022a] and Ding [2025]. Second, whereas Alfaro et al. [2024] leverage sector-level variation in rare earth intensity, we exploit firm-level variation.

3.2 Background and Data

3.2.1 Background

In this section, we explain the background of China's 2010 export restriction, which we use as a natural experiment for the empirical analysis. Appendix C.1 provides more details. In 2010, China imposed export restrictions on rare earths following a diplomatic dispute with Japan over the Senkaku Islands (called Diaoyu in China). The dispute initiated after the captain of a Chinese fishing trawler got arrested by Japanese Coast Guard vessels near the Islands, which strained relationship between two countries. Shortly thereafter, China imposed the restriction on rare earths. Although China officially cited environmental and resource-conservation concerns, many observers believe it was aimed at disrupting Japan's high-tech sectors, which depended heavily on Chinese supplies.

In 2012, the US, the EU, and Japan filed complaints against the restriction with the WTO. China claimed that the export restriction could be justified under the WTO's GATT general exception clause Article XX, for the purpose of natural resource conservation and the protection of public health. However, the WTO viewed that the restriction violated international trade rules—favoring domestic firms—and the restriction was not applied fairly between domestic and foreign markets, undermining the legitimacy of China's claim for the environmental justification. As a result, the WTO ruled against China and, consequently, China lifted all the export restrictions by mid 2015.

Although the restriction was temporarily imposed from 2011 to 2015, it demonstrated that China was willing to use resource controls as an instrument of statecraft and heightened geopolitical risks, especially given that China dominated rare earths productions. In 2010, China accounted for roughly 97% of global rare earth mining production and controlled 95% of global processing capacity [U.S. Geological Survey, 2011].[3] Consequently, the 2010 restriction caused short-run price spikes and, in the medium run, increased the likelihood of similar episodes recurring.

[3]Critical minerals, including rare earths, generally require two stages before final use: mining and processing. Mining involves extracting and concentrating raw ore from the ground, while processing covers the chemical and metallurgical steps that transform those concentrates into market-ready chemicals, metals, or compounds. Processing demands specialized infrastructure, proprietary technologies, and stringent environmental controls, so it is often far more geographically concentrated than mining.

3.2.2 Data

Our main dataset comes from confidential Census Bureau datasets. We combine firm-level balance sheet data with their import and export information. The combined dataset forms a firm-level panel spanning from 2007 to 2018.[4] We restrict our sample to manufacturing firms (2-digit NAICS codes 31, 32, and 33), since our focus is on firms using rare earth materials as intermediate inputs rather than wholesalers.

The first main dataset is the Longitudinal Firm Trade Transactions Database (LFTTD) which links international trade transactions to individual firms [Bernard et al., 2009, Kamal and Ouyang, 2020]. It records the universe of imported shipments valued over $2,000 USD and exported shipments valued over $2,500 USD of merchandise goods, with information on the destination or source country, quantity, product codes (HS 8-digit codes), and value of shipments at a daily frequency. We aggregate these import and export transactions on an annual basis.

Using the detailed 8-digit codes in the LFTTD, we can identify whether firms import rare earths or other critical minerals. Appendix Table C.1 reports these HS 8-digit codes related to these critical minerals. Although the LFTTD provides HS codes up to 10 digits, each critical mineral's 8-digit heading corresponds to exactly one 10-digit code. For simplicity and consistency, we therefore classify products using their 8-digit codes.

The main balance sheet dataset comes from the Longitudinal Business Database (LBD). The LBD includes annual information on employment, pay roll, location, and industry affiliation for the universe of private non-farm establishments operating in the US, with firm identifiers [Jarmin and Miranda, 2002]. Because our unit of analysis is at the firm level, we aggregate establishment-level employment and payroll data to the firm level. We also supplement the LBD with revenue data from tax records, constructed by Haltiwanger et al. [2016]. When using revenue information, the number of observations drops due to missing revenue information.[5]

3.3 Empirical Analysis

Treatment and control groups The treatment group consists of US firms that have imported rare earths at least once between 2007 and 2010. The control group consists of firms that have

[4] We use data up to 2018 to avoid the period when US-China trade tensions escalated and to exclude the impact of the pandemic.

[5] Haltiwanger et al. [2016] describes how they link two datasets in detail. The revenue data is sourced from the Census Bureau's Business Register, based on administrative data from annual business income tax records. Overall, they matched two datasets over 80 percent of samples in the LBD. Although selection due to non-randomness of missing sample can be an issue, Haltiwanger et al. [2016] find that the pattern of missingness of revenue is only weakly related to observable firm characteristics such as firm age and size, implying that selection is unlikely to be a big concern.

imported 7 different critical minerals but not rare earths: Tungsten, Molybdenum, Cobalt, Nickel, Graphite, Copper, and Lithium.[6] This choice of the control group is defined based on DOI:22 and IEA:24. These reports list these 8 minerals (rare earth and 7 control minerals) as their list of critical minerals, based on the supply chain risks due to high concentration by China, the size of their downstream sectors, and their importance for rising energy technologies (e.g., batteries and electric vehicles).[7] BRICS and other G7 countries have similar lists of critical minerals [Evenett and Fritz, 2023].

Table 3.1: Descriptive Statistics. Treated and Control Groups in 2010

Variables	Avg. emp.	Avg. wage (2010 USD)	Shares of exporters (%)	Number of firms
	(1)	(2)	(3)	(4)
Treated group	4293	75480	98	150
Control group	1841	72760	94	500

There are two advantages to our natural experiment and control group design. First, because the 2010 restriction arose from the diplomatic dispute between China and Japan rather than from China's relations with the US, it is unlikely to correlate with US-specific factors. Second, the control minerals faced similar global demand shocks (e.g., advances in electric-vehicles; see Appendix Table C.2 for detailed industrial uses) and China's comparable dominance in these minerals made them also vulnerable to geopolitical risks. For example, China accounted for about 80% of global graphite mine output and 90% of processing capacity, levels comparable to its shares in rare earths. Similar patterns hold for the other critical minerals. Appendix Figure C.2 shows China's market concentration in mining and processing for these minerals in 2023.

Table 3.1 reports the descriptive statistics of the treated and control groups in 2010. Treated firms tended to have larger employment than the control group, but the had similar levels of average wage (wage bills divided by total employment) and shares of exporters.

Event study specification for the LBD sample Using the constructed treatment and control groups, we estimate event study models that capture dynamic treatment effects. We consider the

[6]For firms importing both rare earths and other critical minerals, we treat those samples as treated firms.
[7]The DOI used a methodology developed by U.S. Geological Survey [2021].

following two specifications:

$$y_{ft} = \sum_{\tau=-4}^{8} \beta^{\tau} \big(D_t^{\tau} \times \mathbf{1}[\text{Treated}_f] \big) + \delta_i + \delta_{jt} + \epsilon_{ft}, \tag{3.1}$$

where f denotes firm and t calendar years. $D_t^{\tau} = \mathbf{1}[t - \tau = 2010]$ are the event study variables, and $\mathbf{1}[\text{Treated}_f]$ is a dummy for the treatment group. δ_i and δ_{jt} are firm and NAICS 2-digit-by-year fixed effects, respectively. ϵ_{ft} is the error term. Standard errors are clustered at the NAICS 3-digit level.

For some dependent variables with statistical zeros (e.g., exports and imports), we consider the following analogous Poisson pseudo-maximum likelihood (PPML) specification [Silva and Tenreyro, 2006]:

$$y_{ft} = \exp\Big(\sum_{\tau=-4}^{8} \beta^{\tau} \big(D_t^{\tau} \times \mathbf{1}[\text{Treated}_f] \big) + \delta_i + \delta_{jt} + \epsilon_{ft} \Big). \tag{3.2}$$

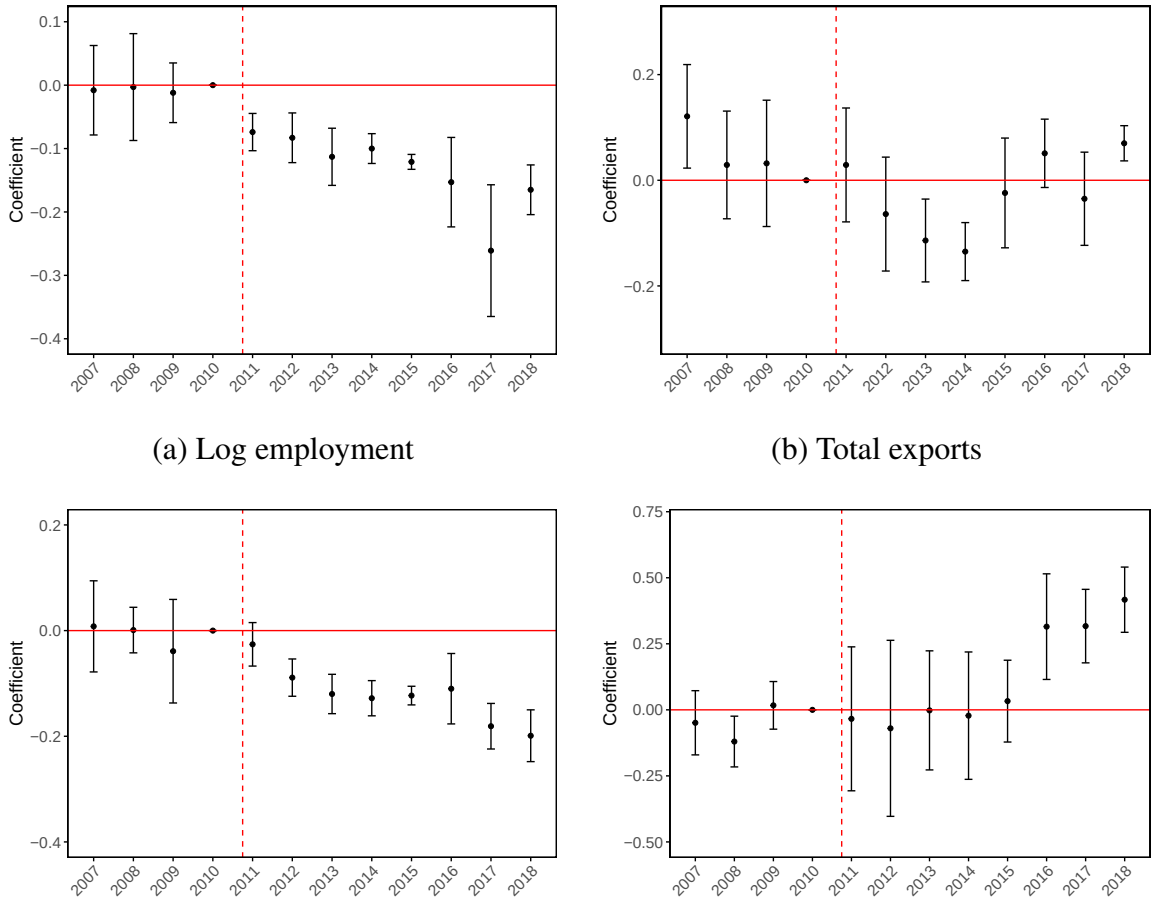
The dynamic coefficients β^{τ} allow us to track dynamic effects of the event using the post-event coefficients and to examine pre-trends using the pre-event coefficients. Because the event occurred for all treated firms in 2010, we do not face the issues associated with the recent staggered diff-in-diff literature [Roth et al., 2023].

Figure 3.2 shows the impact of rare earth supply shock on select firm outcomes. As panel (a) of figure 3.2 shows, despite the export quota being removed in 2015, firms' employment continued to fall. One year after the restriction, employment had dropped by 9%. 8 years later, rare earth importers' employment were still down by 16%.[8] As panel (b) of figure 3.2 shows, the decline in total exports of treated firms was temporary. Rare earth importers saw total export values fall by 15 percent in 2014 before returning to pre-event levels post-2015. A comparable pattern holds for the export participation dummy (see appendix Figure C.3). Moreover, the pre-event coefficients for both outcomes exhibit no pre-trends, supporting our identifying assumption.

The temporary decline in total exports shows in panel (b) of figure 3.2 masks the heterogeneity in the extensive an intensive margin. We find a persistent reduction in the number of products exported by treated firms (see figure 3.2 panel (c)). Consequently, panel (d) shows that export values per product increased in the medium term. The event-study coefficients for export values per product remain close to zero from 2011 to 2015 because aggregate export values temporarily fell. Once aggregate exports returned to pre-shock levels in 2016, the sustained drop in exported products produced positive and statistically significant coefficients. These findings imply that declines

[8] These persistent results are consistent with Cox [2023], Choi and Shim [2024], and Choi and Levchenko [2025] who find persistent effects of temporary tariffs or industrial policy.

Figure 3.2: Event Study. The Effects of the 2010 China's Quota on US Rare Earth Importers' Outcomes



(a) Log employment

(b) Total exports

(c) Number of exported products

(d) Export values per product

Note: This figure reports the estimated coefficients of equations (3.1) or (3.2) with 95% confidence intervals based on standard errors clustered at the NAICS 4-digit levels. The dependent variables are log employment, total exports, the number of exported products, and export values per products in Panels (a), (b), (c), and (d), respectively. The 2010 coefficient β^0 is normalized to zero. All specifications include firm and NAICS 2-digit-by-year fixed effects.

in employment reflect firms' efforts to restructure their production processes. Changes in export composition occurred broadly across product categories. Appendix Figure C.4 shows the number of exported products in six groups (electrical equipment, machinery, metals, mineral products and chemicals, transportation equipment and other goods) where the first five categories are strategic industries often linked to national security and high-tech applications [Freund et al., 2024]. Across all six groups, we observe similar shifts in export product composition.

Discussion To summarize, the persistent declines show that export restrictions can have long-lasting effects beyond short-term price spikes by altering expectations about future policies. In our context, China's rare-earth dominance and the risk of repeating export controls likely led US importers to anticipate further disruptions and restructure their product offerings. These findings highlight the need to account for expectations [Alessandria et al., 2025] and uncertainty [Pierce and Schott, 2016, Handley and Limão, 2017] about future policy changes when evaluating policy impacts.

Moreover, firms focusing on smaller set of core products highlight that firms' restructuring their production processes as adaptation margins to geopolitical risks. This narrowing of product lines left total export values largely unchanged but drove down overall employment. This suggests interdependence of production across different products within firms and shows the importance of understanding such adaptation margins for trade policy. These results also align with Ding et al. [2022a] and Ding [2025] who studied the interdependence of production across products through intangible capital among US firms using the Census datasets.

Finally, the temporary decline in rare-earth imports highlights the difficulty of diversifying supply sources under China's near-monopoly. While diversification remains important in principle, when it is practically difficult, policymakers can help firms enhance resilience to the shock through other margins, such as adjusting their product mixes, as we document, or pursuing directed innovation that substitute away from rare earth inputs, as in Alfaro et al. [2024].[9]

3.4 Conclusion

Using firm-trade linked confidential US microdata and the 2010 China's rare earth export restrictions as a natural experiment, we provide first micro-level evidence on how US firms respond to

[9]We broadly view that our changes in product mixes as consistent with the directed innovation consequences documented by Alfaro et al. [2024], because these changes in product mixes may reflect such innovation consequences. However, when we examine service-sector employment shares and R&D employment shares, common proxies for firms' knowledge inputs and innovation intensity [e.g. Fort et al., 2018, Ding et al., 2022a], we find no significant impact of export restrictions. This discrepancy may arise because directed innovation is better captured by patent activity than by employment-based measures. Analyzing firm-level patent responses to export controls therefore represents a fruitful direction for future research.

such restriction. After the restriction, US rare importers experienced persistent declines employment, even after the price level reverted to the pre-event level, with persistent drops in product mixes and temporary decline in total exports. These results highlight the importance of geopolitical risks and the interdependence of production across different products within firms.

APPENDIX A

Appendix to Chapter 1

A.1 Proofs and Derivations

A.1.1 Deriving wage markdown

Before deriving markdown under different scenarios, it is instructive to write the relationship between wage offered by the firm and labor supply. The value function in equation 1.2, for a worker in establishment e' can be written as

$$\exp(\beta V_t^{e'}) = \left(\frac{w_t^{e'}}{P_t^{e'}}\right)^{\beta} \times \left(\sum_e \exp(\beta V_{t+1}^{e} - \gamma_{e'e})^{1/\nu}\right)^{\nu\beta}$$

Multiplying both sides by $\exp(-\gamma_{ee'})$, taking exponent of $1/\nu$ and expressing $\sum_e \exp(\beta V_{t+1}^{e} - \gamma_{e'e})^{1/\nu} = \Theta_{t+1}^{e'}$

$$\exp(\beta V_t^{e'} - \gamma_{ee'})^{1/\nu} = \exp(-\gamma_{ee'})^{1/\nu} \left(\frac{w_t^{e'}}{P_t^{e'}}\right)^{\beta/\nu} \times \left(\Theta_{t+1}^{e'}\right)^{\beta} \tag{A.1}$$

Substituting equation A.1 in equation 1.3 and 1.4 gives the relationship between wage offered by establishment e' in period t and labor supplied to the establishment in period t.

$$L_t^{e'} = \left(\frac{w_t^{e'}}{P_t^{e'}}\right)^{\beta/\nu} \left(\Theta_{t+1}^{e'}\right)^{\beta} \times \left(\sum_e \frac{\exp(-\gamma_{ee'})^{1/\nu}}{\Theta_t^{e}} L_{t-1}^{e}\right) \tag{A.2}$$

A.1.1.1 Markdown under Bertrand competition and establishment profit maximization

The profit maximization problem of the establishment is given by equation 1.7. Under Bertrand competition, establishments cannot take $\Theta_t^{e'}$ as given, but account for how their wage w_t^e will affect the overall index $\Theta_t^{e'}(w_t^e)$. After substituting CES demand, production function and labor supply equation into the establishment's profit, the maximization problem of the establishment can be written as

$$\max_{w_t^e} \quad A_t^{ns\left(\frac{\eta-1}{\eta}\right)}\Pi_t^e\left(\Theta_{t+1}^e\right)^{\beta\left(\frac{\eta-1}{\eta}\right)}\left(\frac{w_t^e}{P_t^e}\right)^{\frac{\beta}{\nu}\left(\frac{\eta-1}{\eta}\right)}\left(\sum_{e'}\frac{\exp(-\gamma_{ee'})^{1/\nu}}{\Theta_t^{e'}(w_t^e)}L_{t-1}^{e'}\right)^{\left(\frac{\eta-1}{\eta}\right)}$$
$$-\frac{\left(\Theta_{t+1}^e\right)^{\beta}}{(P_t^e)^{\beta/\nu}}\left(w_t^e\right)^{\beta/\nu+1}\left(\sum_{e'}\frac{\exp(-\gamma_{ee'})^{1/\nu}}{\Theta_t^{e'}(w_t^e)}L_{t-1}^{e'}\right).$$

The First Order Condition of the above maximization problem can be written as

$$\begin{aligned}
&A_t^{ns\left(\frac{\eta-1}{\eta}\right)}\Pi_t^e\left(\Theta_{t+1}^e\right)^{\beta\left(\frac{\eta-1}{\eta}\right)}\left[\frac{\beta}{\nu}\frac{\eta-1}{\eta}\frac{\left(w_t^e\right)^{\frac{\beta}{\nu}\left(\frac{\eta-1}{\eta}\right)-1}}{\left(P_t^e\right)^{\frac{\beta}{\nu}\left(\frac{\eta-1}{\eta}\right)}}\left(\Psi_t^e\right)^{\left(\frac{\eta-1}{\eta}\right)}\right.\\
&\left.+\left(\frac{w_t^e}{P_t^e}\right)^{\frac{\beta}{\nu}\left(\frac{\eta-1}{\eta}\right)}\frac{\eta-1}{\eta}\left(\Psi_t^e\right)^{-1/\eta}\left(\sum_{e'}\exp(-\gamma_{ee'})^{1/\nu}\frac{d\left(\frac{1}{\Theta_t^{e'}}\right)}{dw_t^e}L_{t-1}^{e'}\right)\right]\\
&-\frac{\left(\Theta_{t+1}^e\right)^{\beta}}{(P_t^e)^{\beta/\nu}}\frac{\beta+\nu}{\nu}\left(w_t^e\right)^{\beta/\nu}\left(\Psi_t^e\right)\\
&-\frac{\left(\Theta_{t+1}^e\right)^{\beta}}{(P_t^e)^{\beta/\nu}}\left(w_t^e\right)^{\beta/\nu+1}\left(\sum_{e'}\exp(-\gamma_{ee'})^{1/\nu}\frac{d\left(\frac{1}{\Theta_t^{e'}}\right)}{dw_t^e}L_{t-1}^{e'}\right)=0.
\end{aligned}\tag{A.3}$$

where to simplify, $\left(\Psi_t^e\right)=\sum_{e'}\frac{\exp(-\gamma_{ee'})^{1/\nu}}{\Theta_t^{e'}(w_t^e)}L_{t-1}^{e'}$ and $\Pi_t^e=\left(\sum_m\frac{(\tau_{n(e)m})^{1-\eta}}{(P_t^{ms})^{1-\eta}}\kappa_s Y_t^m\right)^{1/\eta}$. Substituting equation A.1 in the definition of $\Theta_{t+1}^{e'}$ i.e. $\sum_e\exp(\beta V_{t+1}^e-\gamma_{e'e})^{1/\nu}=\Theta_{t+1}^{e'}$, one can derive an expression for $\frac{d\left(\frac{1}{\Theta_t^{e'}}\right)}{dw_t^e}$

$$\frac{d\left(\frac{1}{\Theta_t^{e'}}\right)}{dw_t^e}=-\frac{\exp(-\gamma_{ee'})^{1/\nu}}{(\Theta_t^{e'})^2}\frac{\beta}{\nu}\frac{(w_t^e)^{\beta/\nu-1}}{(P_t^e)^{\beta/\nu}}\times\left(\Theta_{t+1}^e\right)^{\beta}\tag{A.4}$$

Now, substituting equation A.4 in equation A.3 and taking a number of steps for simplification, the FOC becomes

$$\begin{aligned}
&A_t^{ns\left(\frac{\eta-1}{\eta}\right)}\Pi_t^e\left(\Theta_{t+1}^e\right)^{-\beta/\eta}\frac{\eta-1}{\eta}\left(\Psi_e^t\right)^{-1/\eta}\frac{\left(w_t^e\right)^{-\beta/(\nu\eta)-1}}{\left(P_t^e\right)^{-\beta/(\nu\eta)}}=\\
&\frac{\left[\frac{\beta+\nu}{\beta}-\frac{(w_t^e)^{\beta/\nu}}{(P_t^e)^{\beta/\nu}}(\Theta_{t+1}^e)^{\beta}\left(\Psi_t^e\right)^{-1}\left(\sum_{e'}\frac{\exp(-\gamma_{ee'})^{2/\nu}}{(\Theta_t^{e'})^2}L_{t-1}^{e'}\right)\right]}{\left[1-\frac{(w_t^e)^{\beta/\nu}}{(P_t^e)^{\beta/\nu}}(\Theta_{t+1}^e)^{\beta}\left(\Psi_t^e\right)^{-1}\left(\sum_{e'}\frac{\exp(-\gamma_{ee'})^{2/\nu}}{(\Theta_t^{e'})^2}L_{t-1}^{e'}\right)\right]}
\end{aligned}\tag{A.5}$$

To get to the markdown from equation A.5, note that markdown $\frac{p_t^e q_t^e}{w_t^e l_t^e}$ using the three constraints in equation 1.7 can be written down as the following

$$MD_t^e = \frac{p_t^e q_t^e}{w_t^e l_t^e} = A_t^{ns(\frac{\eta-1}{\eta})} \Pi_t^e \Big(\Theta_{t+1}^e\Big)^{\frac{-\beta}{\eta}} \times \frac{\big(w_t^e\big)^{\frac{-\beta}{\nu\eta}-1}}{\big(P_t^e\big)^{\frac{-\beta}{\nu\eta}}} \Big(\Psi_t^e\Big)^{\frac{-1}{\eta}} \tag{A.6}$$

However, note that the RHS of equation A.6 can be replaced based on the simplified FOC in equation A.5. This allows me to write the markdown as follows:

$$MD_t^e = \frac{p_t^e q_t^e}{w_t^e l_t^e} = \frac{\frac{\eta}{\eta-1}\Big[\frac{\beta+\nu}{\beta} - \frac{(w_t^e)^{\beta/\nu}}{(P_t^e)^{\beta/\nu}}(\Theta_{t+1}^e)^{\beta}\Big(\Psi_t^e\Big)^{-1} \times \Big(\sum_{e'} \frac{\exp(-\gamma_{ee'})^{2/\nu}}{(\Theta_t^{e'})^2} L_{t-1}^{e'}\Big)\Big]}{\Big[1 - \frac{(w_t^e)^{\beta/\nu}}{(P_t^e)^{\beta/\nu}} \times (\Theta_{t+1}^e)^{\beta}\Big(\Psi_t^e\Big)^{-1}\Big(\sum_{e'} \frac{\exp(-\gamma_{ee'})^{2/\nu}}{(\Theta_t^{e'})^2} L_{t-1}^{e'}\Big)\Big]}$$

Let's define the term inside the brackets above as Φ_t^e, i.e.

$$\Phi_t^e = \frac{(w_t^e)^{\beta/\nu}}{(P_t^e)^{\beta/\nu}}(\Theta_{t+1}^e)^{\beta} \times \frac{\sum_{e'}\Big(\frac{\exp(-\gamma_{ee'})^{1/\nu}}{\Theta_t^{e'}(w_t^e)}\Big)^2 L_{t-1}^{e'}}{\sum_{e'} \frac{\exp(-\gamma_{ee'})^{1/\nu}}{\Theta_t^{e'}(w_t^e)} L_{t-1}^{e'}} \tag{A.7}$$

To simplify the RHS of equation A.7, multiply and divide RHS by $\frac{(w_t^e)^{\beta/\nu}}{(P_t^e)^{\beta/\nu}}(\Theta_{t+1}^e)^{\beta}$, take the terms inside the summation and use the fact that equation 1.2 can be manipulated and written as $\exp(\beta V_t^{e'} - \gamma_{ee'})^{1/\nu} = \exp(-\gamma_{ee'})^{1/\nu}\left(\frac{w_t^{e'}}{P_t^{e'}}\right)^{\beta/\nu} \times \Big(\Theta_{t+1}^{e'}\Big)^{\beta}$, which leads to

$$\Phi_t^e = \frac{\sum_{e'}\Big(\frac{\exp(\beta V_t^e - \gamma_{ee'})^{1/\nu}}{\Theta_t^{e'}}\Big)^2 L_{t-1}^{e'}}{\sum_{e'} \frac{\exp(\beta V_t^{e'} - \gamma_{ee'})^{1/\nu}}{\Theta_t^{e'}} L_{t-1}^{e'}} \tag{A.8}$$

However, note that the term $\frac{\exp(\beta V_t^e - \gamma_{ee'})^{1/\nu}}{\Theta_t^{e'}}$ is defined as $\mu_{t-1}^{e \to e'}$ in equation 1.3. This means the markdown can be written succinctly as

$$MD_t^e = \frac{p_t^e q_t^e}{w_t^e l_t^e} = \frac{\frac{\eta}{\eta-1}\Big[\frac{\beta+\nu}{\beta} - \Phi_t^e\Big]}{1 - \Phi_t^e}$$

$$\text{where} \quad \Phi_t^e = \frac{\sum_{e'}\Big(\mu_{t-1}^{e' \to e}\Big)^2 L_{t-1}^{e'}}{\sum_{e'}\Big(\mu_{t-1}^{e' \to e}\Big) L_{t-1}^{e'}}$$

A.1.1.2 Markdown under Bertrand competition and firm profit maximization

I now solve the profit maximization problem of a firm F that contains $i = 1, 2, ..., N$ establishments. In the case where firms set wages to maximize the total profits across all establishments belonging to firm F, the maximization problem can be written down as follows

$$\max_{w_t^1, w_t^2, \ldots, w_t^N} \quad \sum_{i \in F} A_t^{ns(\frac{\eta-1}{\eta})} \Pi_t^i \Big(\Theta_{t+1}^i\Big)^{\beta(\frac{\eta-1}{\eta})} \left(\frac{w_t^i}{P_t^i}\right)^{\frac{\beta}{\nu}(\frac{\eta-1}{\eta})} \Big(\sum_{e'} \frac{\exp(-\gamma_{ie'})^{1/\nu}}{\Theta_t^{e'}(w_t^1, \ldots, w_t^N)} L_{t-1}^{e'}\Big)^{(\frac{\eta-1}{\eta})}$$
$$- \frac{\Big(\Theta_{t+1}^i\Big)^{\beta}}{(P_t^i)^{\beta/\nu}} \left(w_t^i\right)^{\beta/\nu+1} \Big(\sum_{e'} \frac{\exp(-\gamma_{ie'})^{1/\nu}}{\Theta_t^{e'}(w_t^1, \ldots, w_t^N)} L_{t-1}^{e'}\Big)$$

The first order condition for a specific wage, say w_t^1, can be written as follows (with A_t^1 representing the productivity in the location n and sector s of establishment 1, A_t^{ns}):

$$\begin{aligned}
&\Big(A_t^1\Big)^{(\frac{\eta-1}{\eta})} \Pi_t^1 \Big(\Theta_{t+1}^1\Big)^{\beta(\frac{\eta-1}{\eta})} \Bigg[\frac{\beta}{\nu}\frac{\eta-1}{\eta}\frac{\left(w_t^1\right)^{\frac{\beta}{\nu}(\frac{\eta-1}{\eta})-1}}{\left(P_t^1\right)^{\frac{\beta}{\nu}(\frac{\eta-1}{\eta})}} \Big(\Psi_t^1\Big)^{(\frac{\eta-1}{\eta})} \\
&+ \left(\frac{w_t^1}{P_t^1}\right)^{\frac{\beta}{\nu}(\frac{\eta-1}{\eta})} \frac{\eta-1}{\eta} \Big(\Psi_t^1\Big)^{-1/\eta} \Big(\sum_{e'} \exp(-\gamma_{1e'})^{1/\nu} \frac{d\left(\frac{1}{\Theta_t^{e'}}\right)}{dw_t^1} L_{t-1}^{e'}\Big)\Bigg] \\
&- \frac{\Big(\Theta_{t+1}^1\Big)^{\beta}}{(P_t^1)^{\beta/\nu}} \frac{\beta+\nu}{\nu} \left(w_t^1\right)^{\beta/\nu} \Big(\Psi_t^1\Big) \\
&- \frac{\Big(\Theta_{t+1}^1\Big)^{\beta}}{(P_t^1)^{\beta/\nu}} \left(w_t^1\right)^{\beta/\nu+1} \Big(\sum_{e'} \exp(-\gamma_{1e'})^{1/\nu} \frac{d\left(\frac{1}{\Theta_t^{e'}}\right)}{dw_t^1} L_{t-1}^{e'}\Big) \\
&+ \sum_{i \neq 1, i \in F} \Big(A_t^i\Big)^{(\frac{\eta-1}{\eta})} \Pi_t^i \Big(\Theta_{t+1}^i\Big)^{\beta(\frac{\eta-1}{\eta})} \left(\frac{w_t^i}{P_t^i}\right)^{\frac{\beta}{\nu}(\frac{\eta-1}{\eta})} \frac{\eta-1}{\eta} \Big(\Psi_t^i\Big)^{-1/\eta} \\
&\times \Big(\sum_{e'} \exp(-\gamma_{ie'})^{1/\nu} \frac{d\left(\frac{1}{\Theta_t^{e'}}\right)}{dw_t^1} L_{t-1}^{e'}\Big) \\
&- \frac{\Big(\Theta_{t+1}^i\Big)^{\beta}}{(P_t^i)^{\beta/\nu}} \left(w_t^i\right)^{\beta/\nu+1} \Big(\sum_{e'} \exp(-\gamma_{ie'})^{1/\nu} \frac{d\left(\frac{1}{\Theta_t^{e'}}\right)}{dw_t^1} L_{t-1}^{e'}\Big) = 0
\end{aligned} \tag{A.9}$$

Using equation A.4 to substitute for $\frac{d\left(\frac{1}{\Theta_t^{e'}}\right)}{dw_t^1}$ in equation A.9 and further simplifying, we can write the FOC in equation A.9 succinctly as follows

$$\Big(A_t^1\Big)^{(\frac{\eta-1}{\eta})}\Pi_t^1\frac{\eta-1}{\eta}\frac{1}{w_t^1}\Big(\sum_{e'}\mu_{t-1}^{e'\to 1}L_{t-1}^{e'}\Big)^{(\frac{\eta-1}{\eta})}-\frac{\beta+\nu}{\beta}\Big(\sum_{e'}\mu_{t-1}^{1\to e'}L_{t-1}^{e'}\Big)$$
$$=\sum_{i\in F}\Big(A_t^i\Big)^{(\frac{\eta-1}{\eta})}\Pi_t^i\frac{1}{w_t^1}\frac{\eta-1}{\eta}\Big(\sum_{e'}\mu_{t-1}^{e'\to i}L_{t-1}^{e'}\Big)^{-1/\eta}\Big(\sum_{e'}\mu_t^{e'\to i}\mu_{t-1}^{e'\to 1}L_{t-1}^{e'}\Big)$$
$$-\frac{w_t^i}{w_t^1}\Big(\sum_{e'}\mu_{t-1}^{e'\to i}\mu_{t-1}^{e'\to 1}L_{t-1}^{e'}\Big)$$

Using the definition of markdown from equation A.6 and substituting in the above to simplify further, we can write the markdown of establishment 1 as a function of all establishments in firm F.

$$MD_t^1=\frac{\eta}{\eta-1}\frac{\beta+\nu}{\beta}+\sum_{i\in F}\frac{\Big(\sum_{e'}\mu_{t-1}^{e'\to i}\mu_{t-1}^{e'\to 1}\times L_{t-1}^{e'}\Big)}{\Big(\sum_{e'}\mu_{t-1}^{e'\to 1}\times L_{t-1}^{e'}\Big)}\Big[MD_t^i-\frac{\eta}{\eta-1}\Big] \tag{A.10}$$

Defining the cross term $\Phi_t^{e,i}=\dfrac{\Big(\sum_{e'}\mu_{t-1}^{e'\to i}\mu_{t-1}^{e'\to e}\times L_{t-1}^{e'}\Big)}{\Big(\sum_{e'}\mu_{t-1}^{e'\to e}\times L_{t-1}^{e'}\Big)}$, we can finally express markdown of establishment 1 as a function of markdown of all other establishments, leading to the general expression in equation 1.9. Note that there will be an equation like the one below for each establishment in firm F.

$$MD_t^e=\frac{\frac{\eta}{\eta-1}\Big[\frac{\beta+\nu}{\beta}-\Phi_t^e\Big]}{\Big[1-\Phi_t^e\Big]}+\sum_{i\neq e,i\in F}\frac{\Phi_t^{e,i}}{\Big[1-\Phi_t^e\Big]}\Big(MD_t^i-\frac{\eta}{\eta-1}\Big)$$

A.1.2 From establishment level to aggregate markdowns

Here I show that aggregate markdown in the economy is a wage expenditure weighted average of establishment level markdowns.

$$\begin{aligned}MD_{agg}&=\frac{\sum_e p_e q_e}{\sum_e w_e l_e}\\&=\frac{p_1q_1}{\sum_e w_e l_e}+\frac{p_2q_2}{\sum_e w_e l_e}+\cdots+\frac{p_nq_n}{\sum_e w_e l_e}\\&=\frac{w_1l_1}{w_1l_1}\frac{p_1q_1}{\sum_e w_e l_e}+\frac{w_2l_2}{w_2l_2}\frac{p_2q_2}{\sum_e w_e l_e}+\cdots+\frac{w_nl_n}{w_nl_n}\frac{p_nq_n}{\sum_e w_e l_e}\\&\implies MD_{agg}=\sum_e s_e MD_e\end{aligned}$$

where s_e is the share of wage bill for establishment e in the total wage bill across all establish-

ments.

A.1.3 Solution algorithms

A.1.3.1 Steady state equilibrium

1. Start with a guess of the value function for each establishment $V^e_{ss,\text{guess}}\ \forall e$.
2. Given the guess of the value functions in Step 1, calculate the elements of the transition matrix $\mu^{e\to e'}_{ss}$ using Equation (1.3).
3. Given value functions from Step 1 and transition probabilities from Step 2, calculate L^e_{ss} such that Equation (1.4) holds.
4. Using results from Steps 1–3, solve for establishment-specific markdowns MD^e_{ss} from Equation (1.9). Note that wages are not needed to solve for markdowns.
5. Using results from Steps 1–4, solve for wages using Equations (1.10) and (1.11).
6. Using wages from Step 5, calculate implied value functions $V^e_{ss,\text{implied}}$ using Equation (1.2). Go back to Step 1 and update $V^e_{ss,\text{guess}}$ based on $V^e_{ss,\text{implied}}$. Iterate until convergence.

A.1.3.2 Dynamic equilibrium

1. Start by solving the steady-state equilibrium in Section A.1.3.1.
2. Use the steady-state value function V^e_{ss} from Step 1 as the initial guess for the value function V^e_t for all $t = 1 : T$. Use L^e_1 as the initial value of labor.
3. Using V^e_t for $t = 2 : T$, calculate elements of the transition matrix $\mu^{e\to e'}_t$ using Equation (1.3) for $t = 1 : T - 1$.
4. Using $\mu^{e\to e'}_t$ from Step 3 and initial labor L^e_1, compute L^e_t for $t = 2 : T$.
5. Using $\mu^{e\to e'}_t$ and L^e_t for $t = 1 : T - 1$, solve for establishment-specific markdowns MD^e_{t+1} for $t = 1 : T - 1$ from Equation (1.9). Note again that wages are not needed to solve for markdowns.
6. Using MD^e_t and L^e_t for $t = 2 : T$, solve for wages w^e_t for $t = 2 : T$ using Equations (1.10) and (1.11).
7. Given wages and prices from Step 6, calculate the implied value function $V^e_{t,\text{implied}}$ for $t = 2 : T$ using Equation (1.2). Go back to Step 1 and update $V^e_{t,\text{guess}}$ based on $V^e_{t,\text{implied}}$. Iterate until convergence.

A.2 Exploiting the expiration of Multi-Fiber agreement as a negative trade shock

In this section, I exploit the expiration of the Multi-Fiber Agreement (MFA) in 2005 to test whether import shocks differentially affect workers of multi-establishment firms relative to workers of single-establishment firms. While recent work such as Sharma [2023] studies the impact of the expiration of MFA on workers, I study whether treated workers were differentially affected based on whether they worked for a single or multi-establishment firm.

A.2.1 Background

The MFA governed the exports of textile and clothing products from developing to developed countries between 1974 and 2004. In the Uruguay round in 1994, WTO members decided to lift the quotas over four phases spanning 10 years: 1995, 1998, 2002, 2005. In practice, most quotas were reserved for expiration in the last phase [Brambilla et al., 2010].

The export quotas were particularly binding on China and not on other developing countries. For example, at the end of 2004 right before the expiration of the MFA, the share of HS6-digit products facing a quota was 62% for China and only 14% for Brazil. Conditional on having a quota, Chinese exports were much more likely to be binding, with 55% of HS 6-digit products facing a fill rate of greater than 90% (fill-rate is the share of quota actually utilized). The share of binding product lines conditional on a quota was only 5% on Brazil.

This provides an ideal setting to study the impact of a sector specific shock on workers, with the availability of useful control group. At the product level, there were two kinds of textile products. First group of products were those on which China faced binding quotas, removal of which in 2005 would expose producers of those products around the world to competition from Chinese exports. Second group of textile products were those on which China either did not face a quota, or faced a quota which was not binding. The expiration of the MFA in 2005 would have no impact on producers of these products. Given that the two groups of products were similar, one would expect the workers making those products to also be similar. I now describe the data used to study the impact of MFA expiration on workers.

A.2.2 Data, sample and treatment definitions

To do this, I combine three datasets: (i) bindingness of export quota for products under MFA from data complied by US Office of Textiles and Apparel (OTEXA)[1]. (ii) Establishment level exports at

[1] I download this data from Peter Schott's website.

the HS 6-digit level from SECEX (Secretaria de Comércio Exterior) of Brazil and (iii) The RAIS dataset described in section 2.2.

Treated vs control products: Given quotas imposed by United States were the most binding on China, I follow Sharma (2023) and define treatment in terms of quotas imposed by the US. OTEXA data provides information on which phase quota was removed and the fill-rate of US quota by country. I consider all products that were ever covered by the MFA. Treated products are those where quota was removed in 2005 and quota on Chinese exports to US was binding before removal (i.e. had a quota fill-rate of $> 90\%$). All other products are classified as control products. This resulted in 125 treated products and 736 control products at the HS 6-digit level.

Treated vs control establishments: While I do not have establishment level exports for year 2004, such data is available for 2001. I define a Brazilian establishment to be a treated establishment if its highest value product exported in 2001 was a treated product. If the highest value product exported was a control product, I classify the establishment as a control establishment. I do not keep establishments that were neither control nor treated. There were 805 control establishments and 417 treated establishments in 2004.

Treated vs control workers: I classify workers as treated or control based on whether they were working for a treated or control establishment in 2004. Table A.20 provides summary statistics for control and treated workers. Given that the sample only includes workers at exporting establishments, it is unsurprising that almost 2/3rd of the workers for both groups worked for multi-establishment firms in 2004.

A.2.3 Results

Before looking at the impact of MFA expiration on treated and control workers, it is instructive to analyze the extent to which China's exports of treated products increased after MFA expiration, and how Brazilian exports evolved. Figure A.15 shows the value of Chinese and Brazilian exports relative to 2004 for both MFA treated and control products. While exported of treated Chinese products boomed relative to control products, exports of Brazilian treated products declined sharply 2004. Brazilian exports of MFA treated products were 50% lower in 2008 relative to 2004. Given that treatment is defined at the product level with respect to US quotas, the effect is even sharper when looking at exports to the US. While Chinese exports of treated products to US increased by 400% by 2008, Brazilian exports to the US declined by almost 90%. Importantly, while the negative shock for Brazilian exports could have been expected, the scale of the shock was not: Diao and Somwaru [2001], for example, were predicting a 6 percent growth rate of Chinese textile and clothing exports following expiration of the MFA. The setting is thus ideal to study the impact of a large unexpected shock on otherwise similar workers.

They main idea of this paper is that when otherwise similar workers that differ based on belonging to a multi or single-establishment firm are affected by similar shocks, the multi-establishment workers are relatively insulated as they have opportunities to transfer to to other, potentially unaffected establishments of their firm. Such opportunities are unavailable to similar workers of single-establishment firms. To test this, I rely on a triple difference specification similar to that in section 1.3.3.2.

$$y_{it} = \sum_{t=2000}^{2011} \alpha_t(T_i \times \mathbf{1}[\text{time=t}]) + \sum_{t=2000}^{2011} \phi_t(M_i \times \mathbf{1}[\text{time=o}]) + \sum_{t=2000}^{2011} \beta_t(T_i \times M_i \times \mathbf{1}[\text{time=t}]) + \gamma_{mt} + \nu_{it} \tag{A.11}$$

y_{it} represents outcome for worker i at time t. $T_i = 1$ if the worker was treated by expiration of MFA, while $M_i = 1$ if worker worked for a multi-establishment firm in year 2004. I control for location-year specific shocks via microregion-year fixed effects γ_{mt}. β_t are the coefficients of the triple difference term of interest, and represent the differential treatment effect of MFA expiration for multi vs single-establishment workers relative to baseline year 2004. Figure A.16 panel (a) plots the β_t coefficient for when the dependent variable is a binary variable for worker dropping from formal labor force. The treated workers are less likely to drop from formal labor force following expiration of the MFA relative to control workers, echoing the findings in panel (a) of figure 1.2. However, as panel (b) of figure A.16 suggests, migration seems to not be a response to MFA shock.

To the extent that there is a differential response to the MFA shock for multi and single-establishment firm workers, it could come not just from both sets of workers being similarly affected but responding differentially due to within firm reallocation opportunities, but also from differential response to the shock itself. For example, treated workers of multi-establishment firms could be insulated from the impact of MFA expiration, relative to single-establishment workers, because their firms are more productive and thus have a weaker passthrough of the shock to workers.

I find that treated establishments belonging to multi-establishment firms are more likely to survive following MFA shock relative to treated establishments of single-establishment firms. Figure A.17 shows the difference in survival probabilities between treated and control establishments. As panel (a) of figure A.17 shows, treated establishments were 10 percentage points less likely to exist 7 years after the expiration of the MFA. However, the results are driven by exit of establishments belonging to single-establishment firms. As panel (c) of figure A.17, MFA treated establishments of multi-establishment firms did not have a higher probability of exit compared to untreated establishments of multi-establishment firms.

The results highlighted in figures A.16 and A.17 are an empirical affirmation of the Melitz

[2003], where exposure to trade leads to the exit of less productive firms. Multi-establishment firms tend to be larger and more productive than single establishment firms. The protection afforded to multi-establishment workers from negative shocks that comes from them being in a more productive firm is another channel through which workers benefit from being in such firms. However, the focus of this paper is the insurance to workers owing simply to the firms' status as multi-establishment, and not differential productivity.

A.3 Additional tables

Table A.1: Summary statistics for firms (2005)

variable	value
Number of industries (Mean)	1.04
Number of locations (Mean)	1.07
Number of plants (Mean)	1.31
Share Multi-location (%)	1.78
Share Multi-establishment (%)	4.18
Firm size (Mean)	14.33
Number of firms (in million)	1.81

Table A.2: Summary statistics for workers (2005)

variable	value
Average annual wage (1995 USD)	5757.51
Tenure (Mean, in months)	60.67
In Multi-location firm (%)	33.09
In Multi-establishment firm (%)	40.55
Share some college (%)	13.45
Share female (%)	39.79
Number of workers (in million)	33.07

Table A.3: Worker transitions across firms and locations (only workers of multi-establishment firms)

	Same location	Different location
Different firm	9.5%	4.3%
Same firm	83.8%	2.4%

Table A.4: Worker transitions of low skilled workers

	Same location	Different location
Different firm	11.4%	4.8%
Same firm	82.8%	1.4%

Table A.5: Worker transitions of high skilled workers

	Same location	Different location
Different firm	11%	4.2%
Same firm	83%	1.7%

Table A.6: Worker transitions across firms and occupations

	Same occupation	Different occupation
Different firm	5.3%	9.4%
Same firm	76.9%	8.4%

Table A.7: Worker transitions across firms and mesoregions

	Same mesoregion	Different mesoregion
Different firm	12.5%	3.3%
Same firm	83.2%	1%

Table A.8: Worker transitions across firms and states

	Same state	Different state
Different firm	14.1%	1.7%
Same firm	83.8%	0.36%

Table A.9: Worker transitions across firms and sectors

	Same sector	Different sector
Different firm	12.4%	3.4%
Same firm	83.4%	0.8%

Table A.10: Hiring in new establishments by firm source (2005)

	From within the firm	From outside the firm
New establishments of existing firms	22.3%	77.7%
New establishments of new firms	-	100%

Table A.11: Hiring in new establishments by locations (2005)

	From the microregion	From outside the microregion
New establishments of existing firms	81.1%	18.9%
New establishments of new firms	87%	13%

Table A.12: Establishment closures (2000 - 2009)

	Multi-establishment at the time of closure	Single-establishment at the time of closure
Only establishment closed	91%	1%
Both establishment and firm closed	9%	99%

Table A.13: Summary statistics for establishment closures (worker level)

	Affected by plant closure		Not affected by plant closure	
Variable	ME before closure	SE before closure	ME before closure	SE before closure
Mean wage (annual, 1995 USD)	10671.08	6089.46	10975.45	6625.99
Share workers with some college	10.05	7.49	10.41	8.72
Share high skilled workers	33.91	32.94	33.98	34.46
Age bin mean	2.98	2.99	2.97	3.02
Tenure mean (months)	96.09	84.57	96.02	83.93
Emp share in ME firms	100	0	100	0
Median establishment size	150	45	276	154
Num of workers	126936	143867	126936	143867

Table A.14: Plant survival and multi-establishment status

Dependent Variables:	$\mathbf{1}[\text{Establishment alive}_{t+1}]$	$\mathbf{1}[\text{Establishment alive}_{t+3}]$	$\mathbf{1}[\text{Establishment alive}_{t+5}]$
	(1)	(2)	(3)
$\mathbf{1}$[Multi-establishment firm]	-0.010***	-0.014***	-0.015***
	(0.001)	(0.002)	(0.005)
Establishment Industry-Year FE	Yes	Yes	Yes
Observations	19,057,835	19,057,835	19,057,835
Mean dep. variable	0.898	0.768	0.668

Note: Regression includes only the first year of observation of each establishment. Each observation is weighted by establishment size. Standard errors clustered at the microregion level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table A.15: Firm survival and multi-establishment status

Dependent Variables:	$\mathbf{1}[\text{Firm alive}_{t+1}]$	$\mathbf{1}[\text{Firm alive}_{t+3}]$	$\mathbf{1}[\text{Firm alive}_{t+5}]$
	(1)	(2)	(3)
$\mathbf{1}$[Multi-establishment firm]	0.025***	0.071***	0.107***
	(0.001)	(0.002)	(0.003)
Firm Industry-Year FE	Yes	Yes	Yes
Observations	14,374,592	14,374,592	14,374,592
Mean dep. variable	0.906	0.782	0.686

Note: Regression includes only the first year of observation of each firm. Each observation is weighted by firm size. Standard errors clustered at the microregion level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table A.16: Commodity shock and wage effects

Dependent Variable:	$\log(\text{wage})_{2007}$	
	(1)	(2)
$\mathbf{1}[\text{Commodity plant in firm}]_{2002}$	0.010	0.000
	(0.008)	(0.007)
$\mathbf{1}[\text{Commodity plant in firm}]_{2002} \times \mathbf{1}[\text{Commodity sector}]_{2007}$		0.104***
		(0.018)
Worker and Firm controls	Yes	Yes
Occupation FE	Yes	Yes
Origin Industry-Origin location FE	Yes	Yes
Observations	3,485,476	3,485,476

Note: Sample is 20% of workers working in a non-commodity sector in 2002 who were still formally employed in 2007. Worker controls include worker wage and tenure at establishment. Firm control includes firm size. Standard errors clustered at the microregion level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.17: Commodity shock and migration

Dependent Variable:	$\mathbf{1}[\text{2007 microregion different than 2002}]$	
	(1)	(2)
$\mathbf{1}[\text{Commodity plant in firm}]_{2002}$	-0.021***	-0.028***
	(0.006)	(0.006)
$\mathbf{1}[\text{Commodity plant in firm}]_{2002} \times \mathbf{1}[\text{Commodity sector}]_{2007}$		0.070***
		(0.022)
Worker and Firm controls	Yes	Yes
Occupation FE	Yes	Yes
Origin Industry-Origin location FE	Yes	Yes
Observations	3,485,476	3,485,476
Mean dep. variable	0.138	0.138

Note: Sample is 20% of workers working in a non-commodity sector in 2002 who were still formally employed in 2007. Worker controls include worker wage and tenure at establishment. Firm control includes firm size. Standard errors clustered at the microregion level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.18: Transition from non-commodity to commodity sector - Intensive margin

Dependent Variable:	$\mathbf{1}[\text{Commodity sector}]_{2007}$	
	(1)	(2)
$\mathbf{1}[\text{Commodity plant in firm}]_{2002}$	0.055***	0.013***
	(0.011)	(0.004)
$\mathbf{1}[\text{Commodity plant in firm}]_{2002} \times \text{Firm emp share in commodity}_{2002}$		0.161***
		(0.031)
Worker and Firm controls	Yes	Yes
Occupation FE	Yes	Yes
Origin Industry-Origin location FE	Yes	Yes
Observations	3,485,476	3,485,476

Note: Sample is 20% of workers working in a non-commodity sector in 2002 who were still formally employed in 2007. Worker controls include worker wage and tenure at establishment. Firm control includes firm size. Standard errors clustered at the microregion level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.19: AKM regression: Wages and number of firm establishments

Dep. variable:	log(wage)		
	(1)	(2)	(3)
Total establishments in firm	-0.0001**	-0.0002***	-0.0002**
	(0.0001)	(0.0001)	(0.0001)
log(firm size)		0.0354***	0.0419***
		(0.0029)	(0.0034)
Worker FE	Yes	Yes	No
Firm FE	Yes	Yes	No
Year-Education level FE	Yes	Yes	No
Age level-Education level FE	Yes	Yes	No
Worker-Firm FE	No	No	Yes
Year FE	No	No	Yes
R^2	0.970	0.970	0.982
Observations	98,110,966	98,110,966	98,110,966

Table A.20: Comparing MFA treated and control workers in 2004

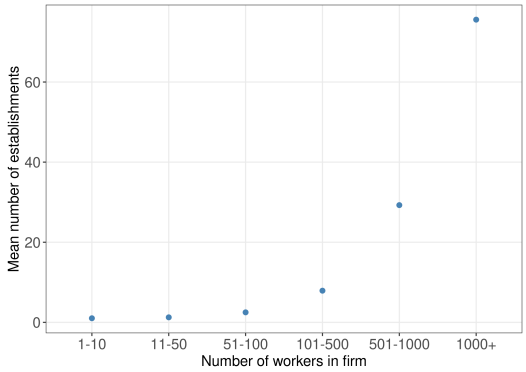
Variable	Not treated	Treated by MFA
Share workers with some college	4.34	3.52
Share high skilled workers	19.45	16.71
Tenure mean (months)	64.34	57.69
Mean wage (annual)	4323.6	3467.29
Emp share in ME firms	65.91	70.04
Num of workers	146380	66338

Table A.21: Mitigation value of multi-establishment firms

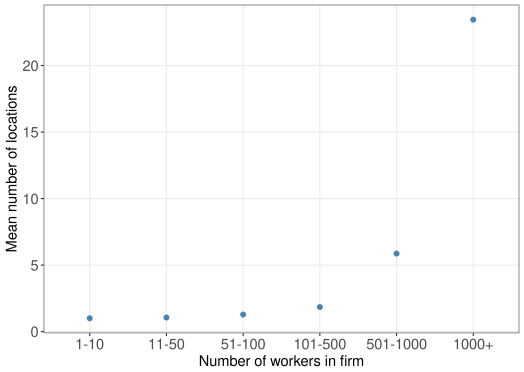
Geography of the shock	Short run			Long run		
	10% shock	20% shock	30% shock	10% shock	20% shock	30% shock
Mesoregion	3.2%	4.8%	6.7%	2.4%	2.7%	3.1%
State	2.1%	3.3%	4.8%	1.8%	2.3%	2.7%
Region	2.1%	2.6%	3.3%	1.2%	1.3%	1.2%

A.4 Additional figures

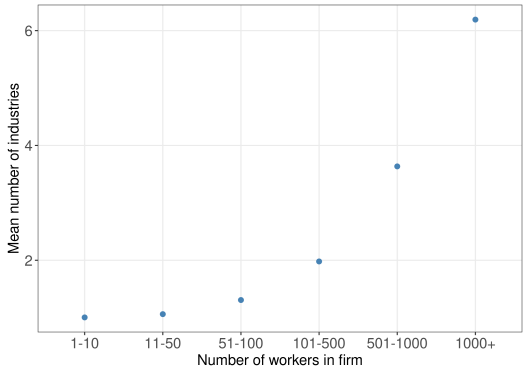
Figure A.1: Establishments, locations and industries by firm size in 2005



(a) Establishments

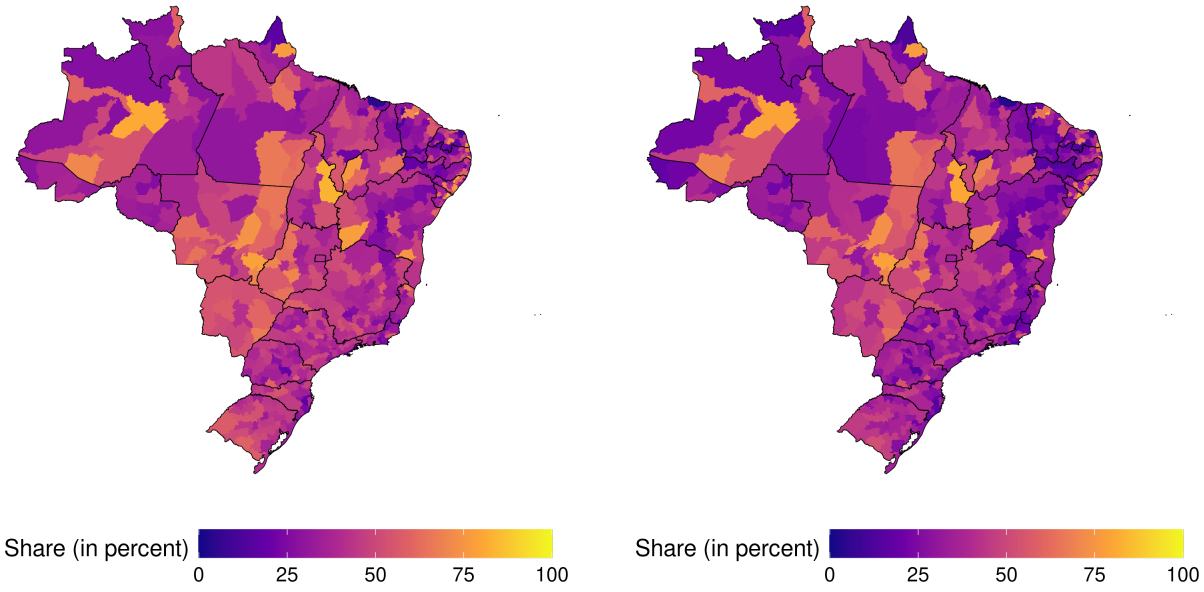


(b) Locations



(c) Industries

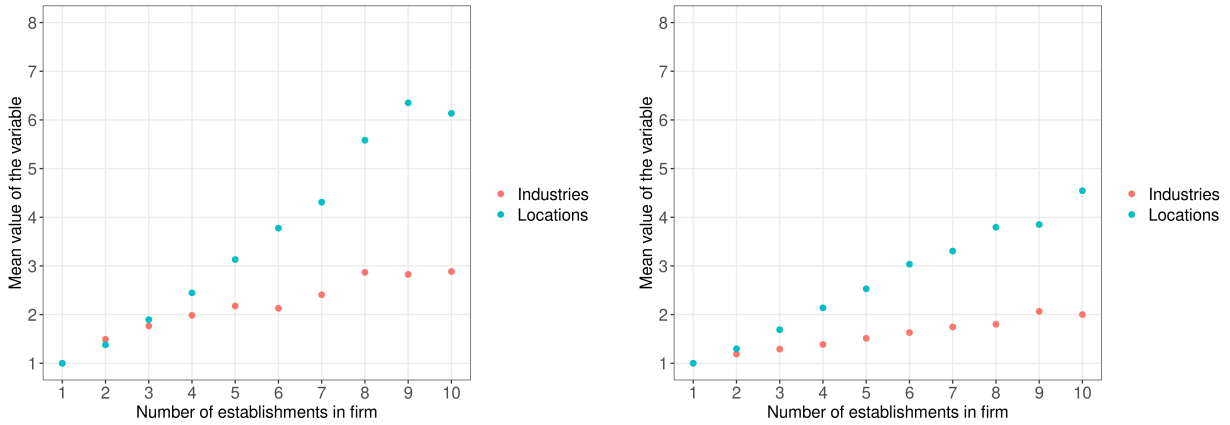
Figure A.2: Employment share by firm type in 2005 (microregion level)



(a) In multi-establishment firms

(b) In multi-location firms

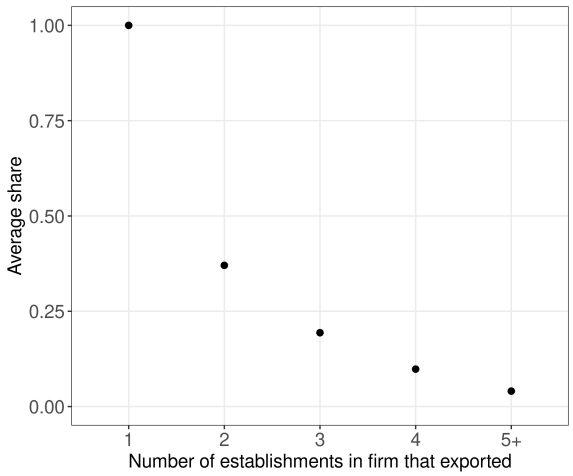
Figure A.3: Locations and sectors by number of firm establishments in 2005



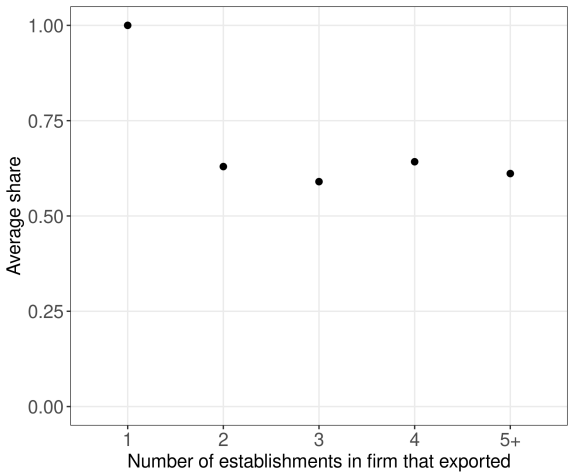
(a) Only manufacturing firms

(b) Only service firms

Figure A.4: Products exported by number of establishments (2001)

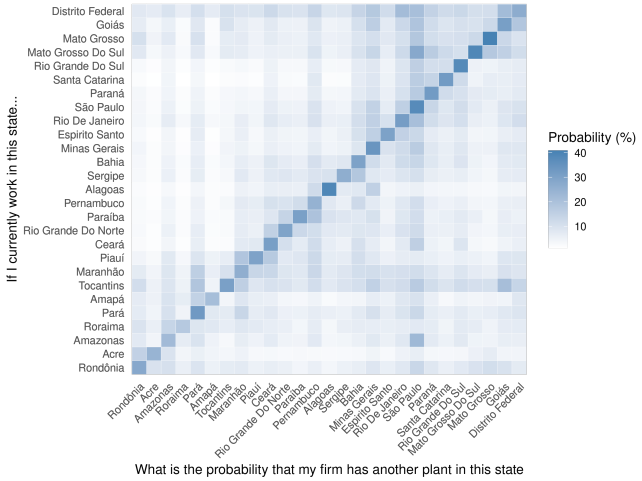


(a) Share of products exported by all establishments

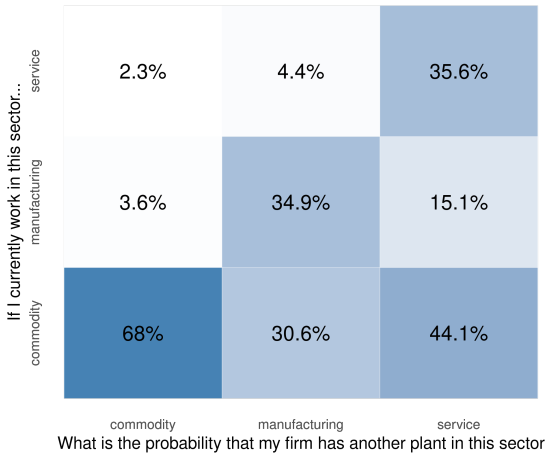


(b) Share of products exported by only one establishment

Figure A.5: Links across sectors and states via multi-establishment firms in 2005

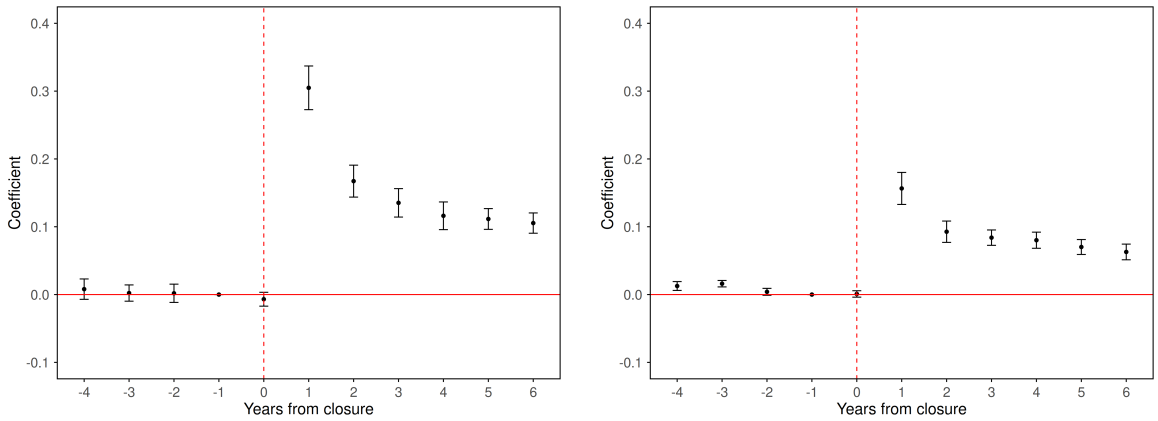


(a) States



(b) Sectors

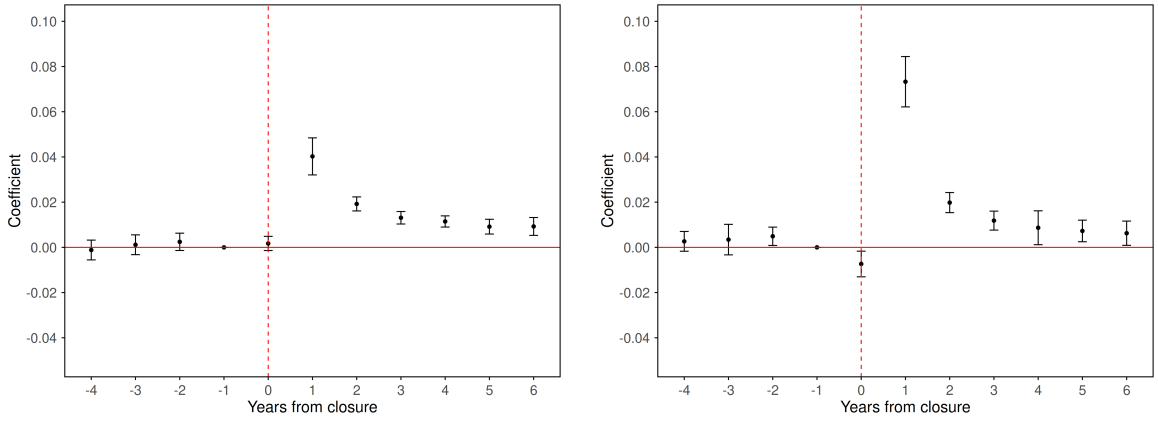
Figure A.6: Dropping from labor force in response to establishment closures



(a) Single-establishment at $t = 0$ (b) Multi-establishment at $t = 0$

Note: These figures plot estimates from a DiD estimator for $t \in [-4, 6]$ (with $t = -1$ omitted). Both figures capture the treatment effect of establishment closure, separately for workers in single and multi-establishment firms. The control group includes matched workers who did not face establishment closure. Error bars show 95% confidence intervals from clustering at the microregion of the worker prior to establishment closure.

Figure A.7: Migration in response to establishment closures



(a) Single-establishment at $t = 0$ (b) Multi-establishment at $t = 0$

Note: These figures plot estimates from a DiD estimator for $t \in [-4, 6]$ (with $t = -1$ omitted). Both figures capture the treatment effect of establishment closure, separately for workers in single and multi-establishment firms. The control group includes matched workers who did not face establishment closure. Error bars show 95% confidence intervals from clustering at the microregion of the worker prior to establishment closure.

Figure A.8: IHS Wages in response to establishment closures

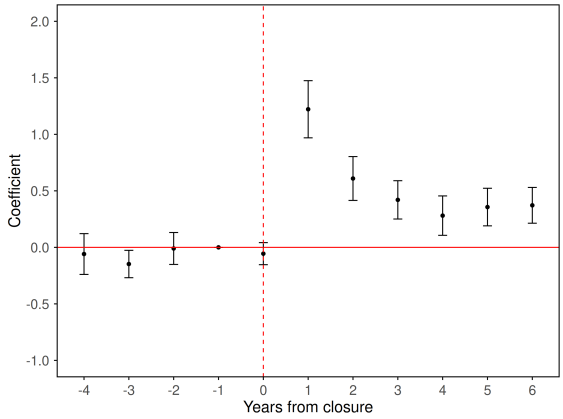


Figure A.9: Relative wages and establishment closure

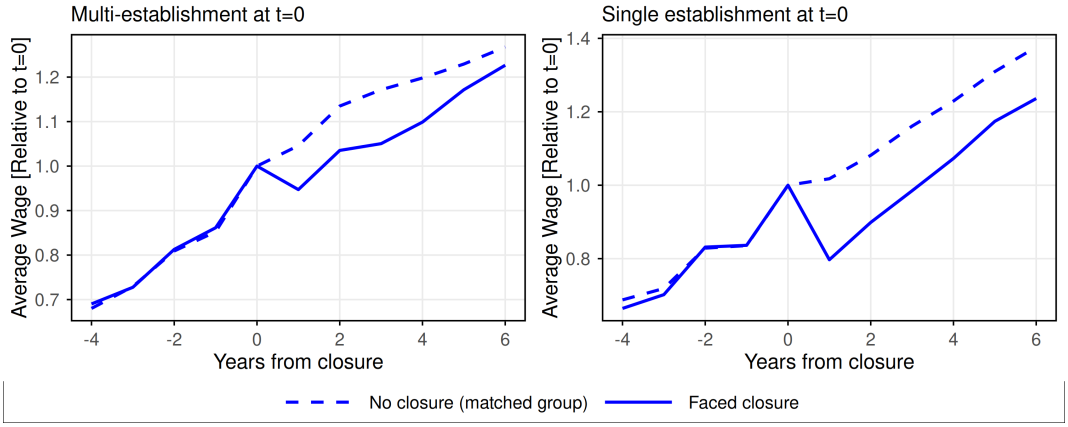


Figure A.10: Raw wages and establishment closure

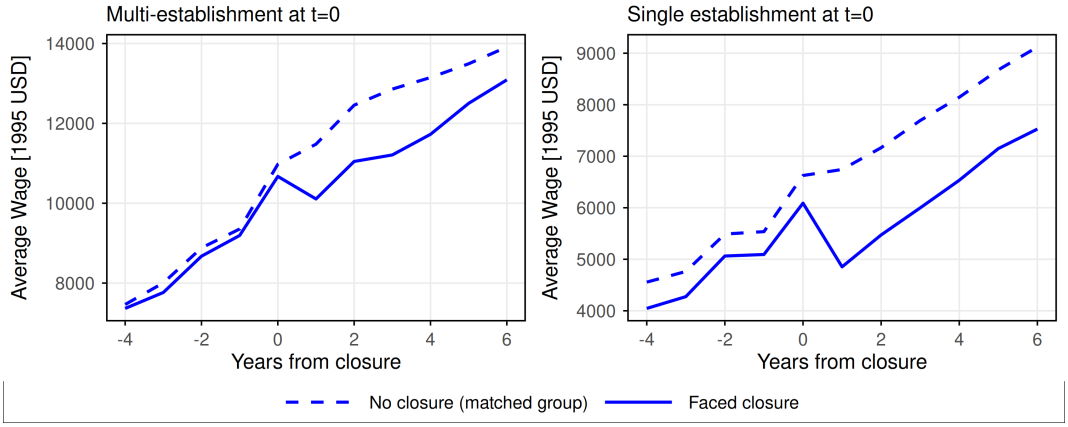
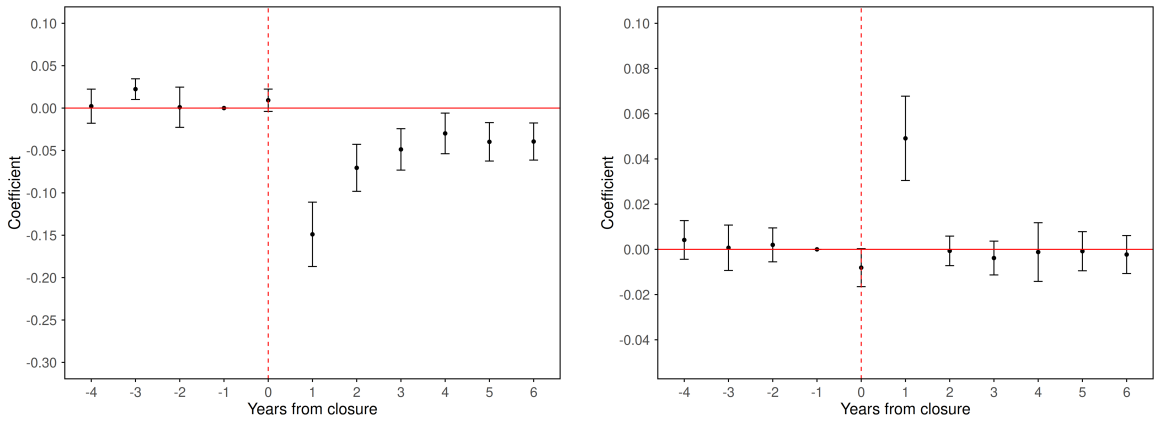


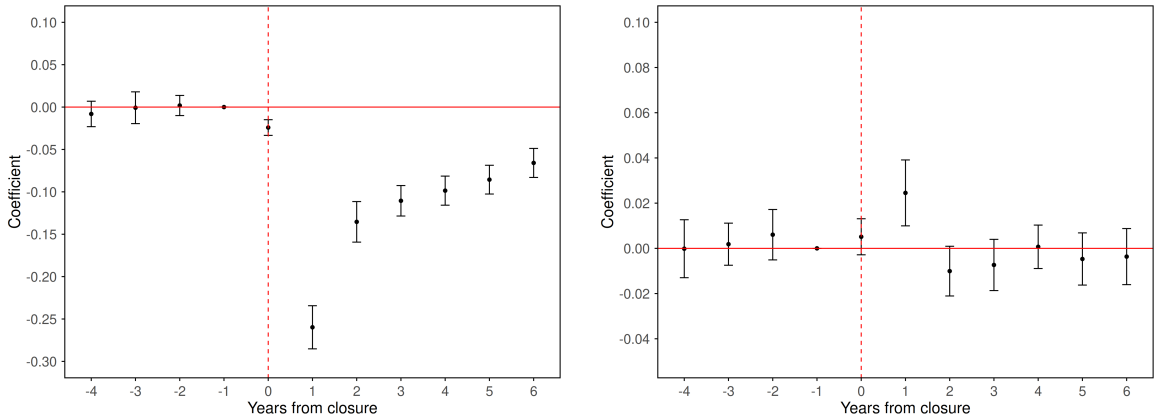
Figure A.11: Worker level response to establishment closures: Service sector only



(a) Dep. variable: $\mathbf{1}[\text{Not in formal LF}]_{it}$ (b) Dep. variable: $\mathbf{1}[\text{Migrated}]_{it}$

Note: These figures plot estimates of β_o from the DDD estimator in equation (1) for $o \in [-4, 6]$ (with $o = -1$ omitted). The sample only includes workers working in service sector in the period before closure. The binary dependent variable in panel (a) is 1 if worker is not in the formal labor force. The binary dependent variable is panel (b) is 1 if the location of the worker is different in current period relative to previous period. Error bars show 95% confidence intervals from clustering at the microregion of the worker prior to establishment closure.

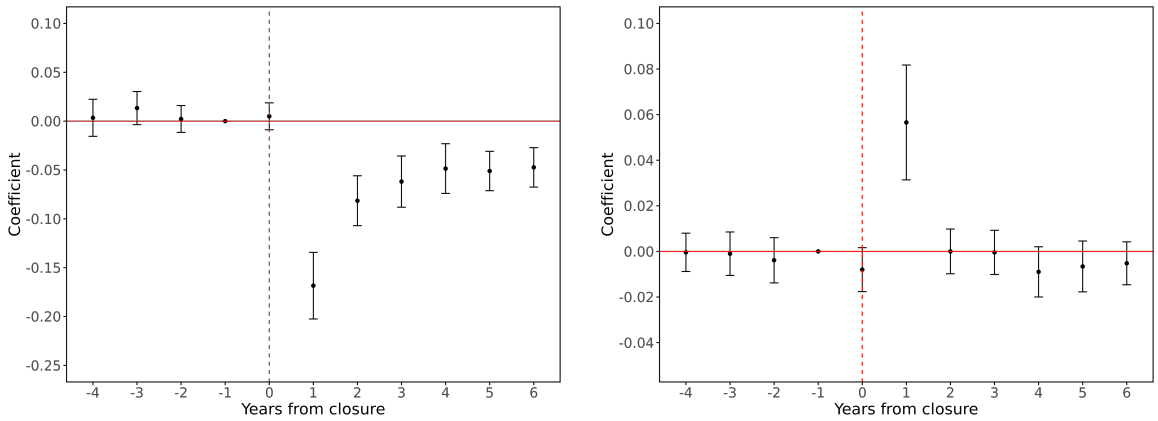
Figure A.12: Worker level response to establishment closures: Wholesale and retail sector only



(a) Dep. variable: $\mathbf{1}[\text{Not in formal LF}]_{it}$ (b) Dep. variable: $\mathbf{1}[\text{Migrated}]_{it}$

Note: These figures plot estimates of β_o from the DDD estimator in equation (1) for $o \in [-4, 6]$ (with $o = -1$ omitted). The sample only includes workers working in the wholesale or retail sector in the period before closure. The binary dependent variable in panel (a) is 1 if worker is not in the formal labor force. The binary dependent variable is panel (b) is 1 if the location of the worker is different in current period relative to previous period. Error bars show 95% confidence intervals from clustering at the microregion of the worker prior to establishment closure.

Figure A.13: Worker level response to location closures



(a) Dep. variable: $\mathbf{1}[\text{Not in formal LF}]_{it}$ (b) Dep. variable: $\mathbf{1}[\text{Migrated}]_{it}$

Note: These figures plot estimates of β_o from the DDD estimator in equation (1) for $o \in [-4, 6]$ (with $o = -1$ omitted). $T_i = 1$ if the worker was affected by a location closure, while $M_i = 1$ if worker worked for a multi-location firm in year $t = 0$. Error bars show 95% confidence intervals from clustering at the microregion of the worker prior to establishment closure.

Figure A.14: Continuing with the same firm after location closure

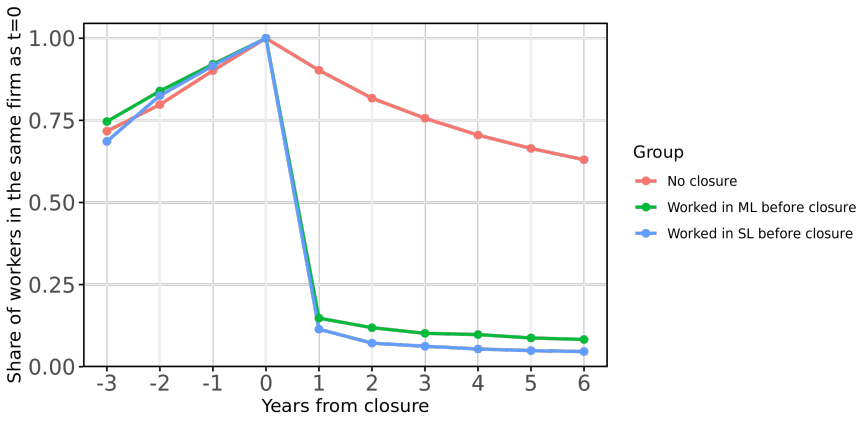


Figure A.15: Chinese and Brazilian exports after MFA expiration

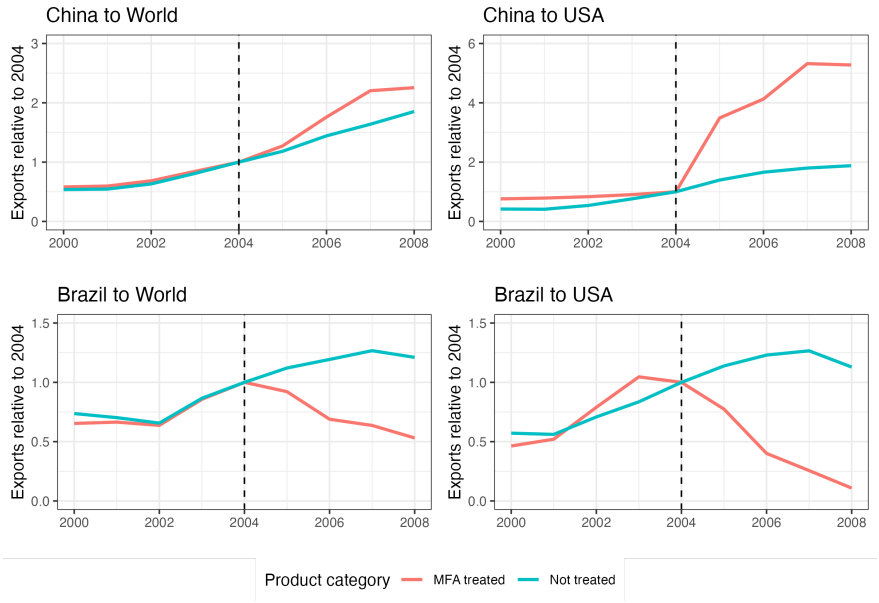
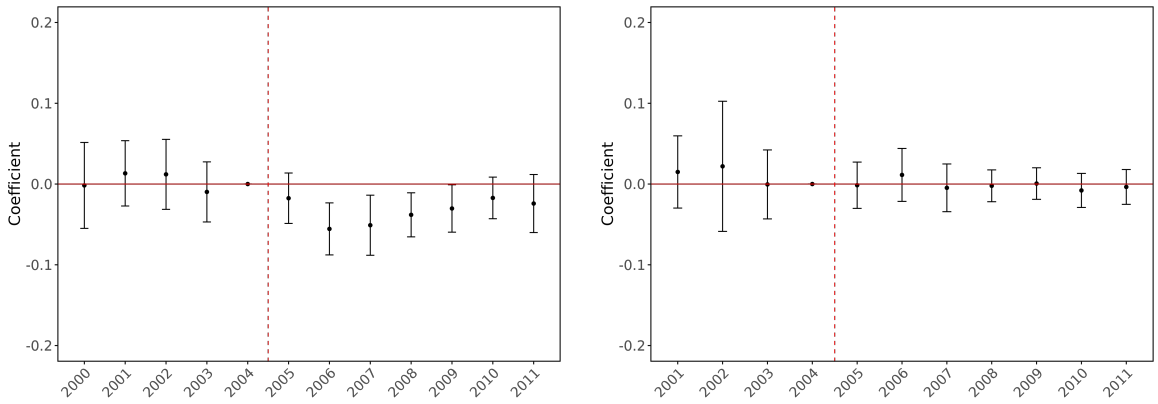


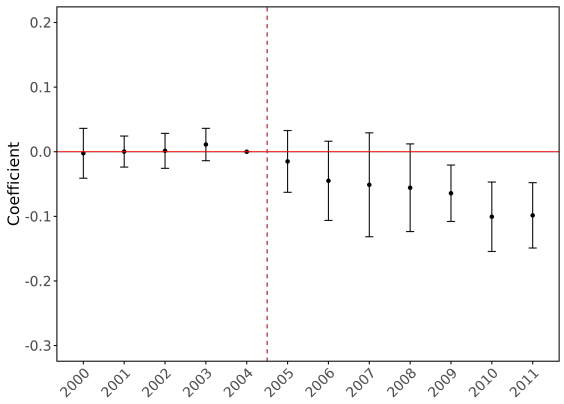
Figure A.16: Worker level response to MFA expiration



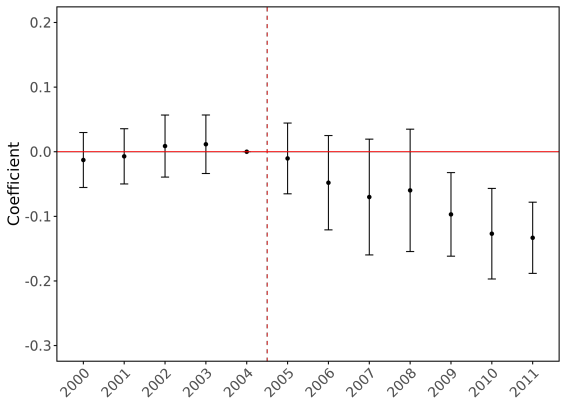
(a) Dep. variable: $\mathbf{1}[\text{Not in formal LF}]_{it}$ (b) Dep. variable: $\mathbf{1}[\text{Migrated}]_{it}$

Note: These figures plot estimates of β_o from the DDD estimator in equation (22) for $o \in [-4, 6]$ (with $o = -1$ omitted). The binary dependent variable in panel (a) is 1 if worker is not in the formal labor force. The binary dependent variable is panel (b) is 1 if the location of the worker is different in current period relative to previous period. Error bars show 95% confidence intervals from clustering at the microregion of the worker in 2004.

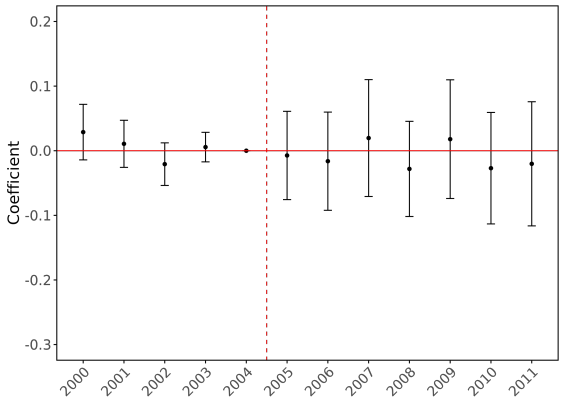
Figure A.17: Establishment survival in response to MFA expiration



(a) All establishments



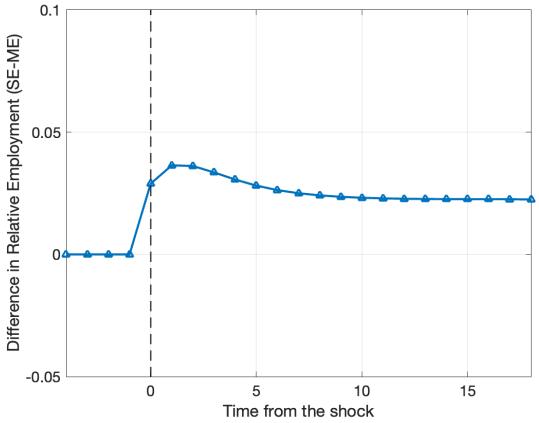
(b) Establishments of SE firms



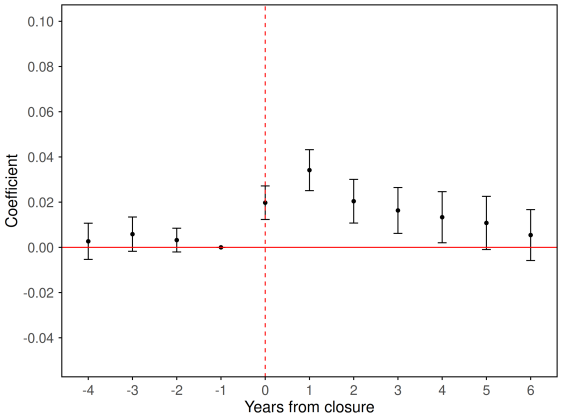
(c) Establishments of ME firms

Note: The figures show establishment level treatment effect of the expiration of Multi-Fiber agreement on establishment survival. Panel (a) plots the treatment effect for all establishments. Panel (b) and (c) show treatment effect separately for establishments of single and multi-establishment firms. Error bars show 95% confidence intervals from clustering at the microregion of the establishment in 2004.

Figure A.18: Impact of negative productivity shock: multi vs single-establishment workers

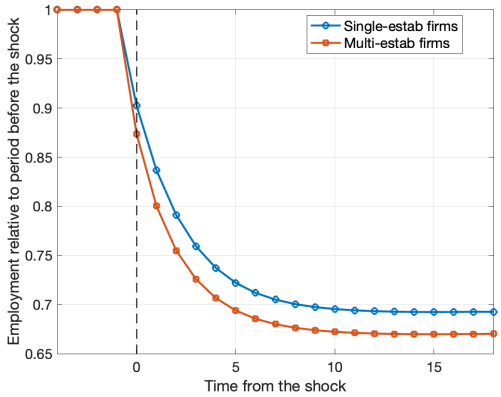


(a) Difference in relative employment (model)

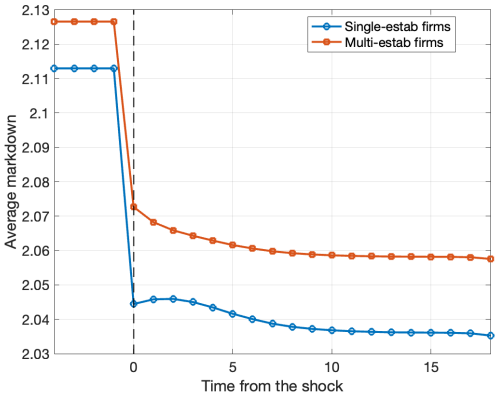


(b) $\mathbf{1}[\text{loc different than } t-1]_{it}$ (data)

Figure A.19: Difference between single and multi-establishment firms in shocked location

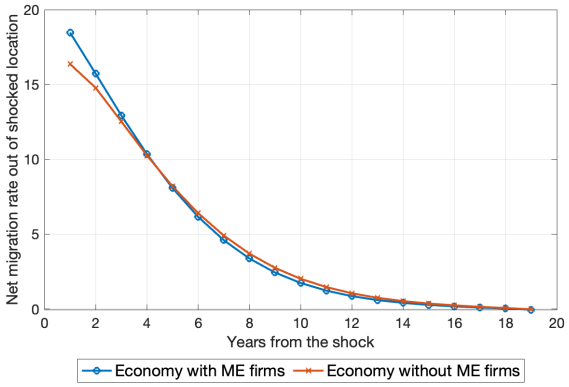


(a) Relative employment

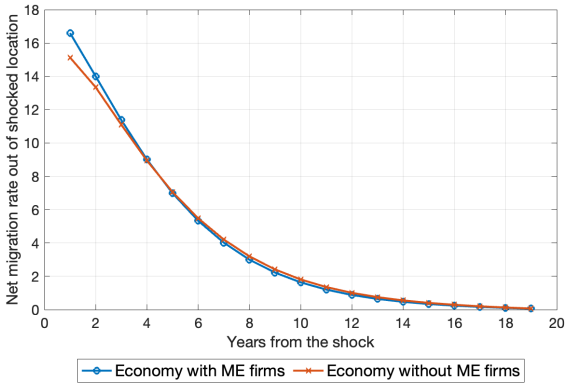


(b) Markdown (Service sector only)

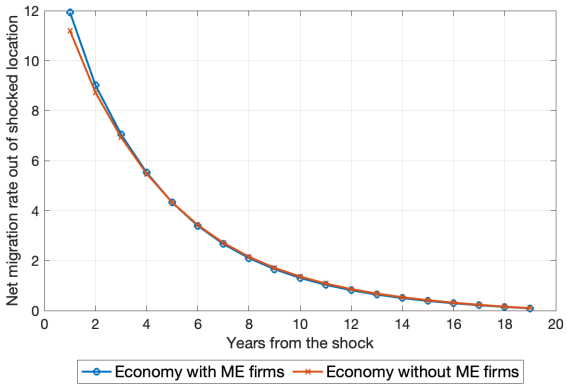
Figure A.20: Impact of negative productivity shocks on migration in shocked location



(a) Mesoregion shock



(b) Region shock



(c) State shock

Figure A.21: Transition to non-employment from shocked locations

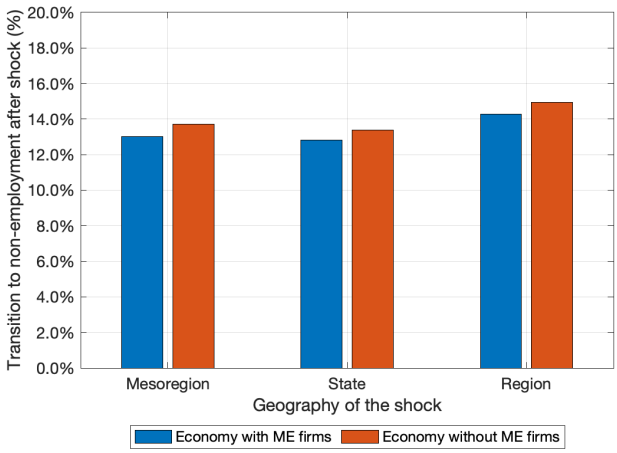
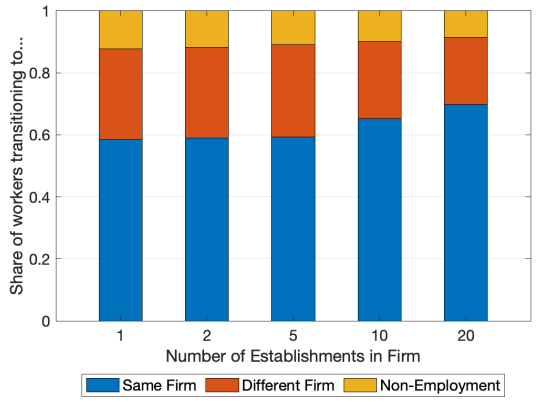
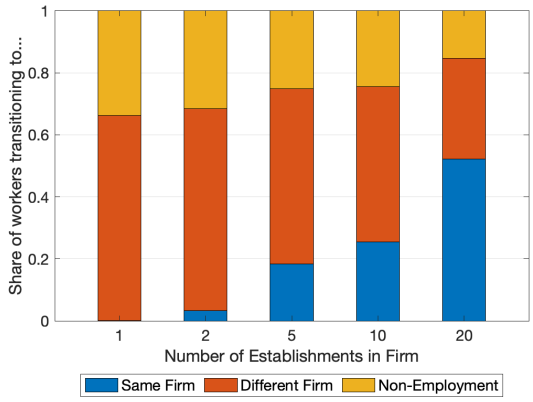


Figure A.22: Worker transition after shock



(a) -20% productivity shock



(b) Establishment closure

APPENDIX B

Appendix to Chapter 2

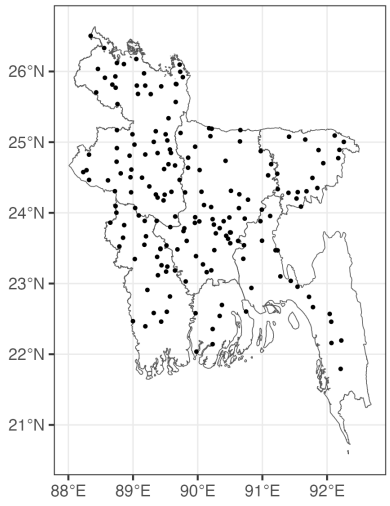
B.1 Data appendix

B.1.1 Construction of the flooding shocks

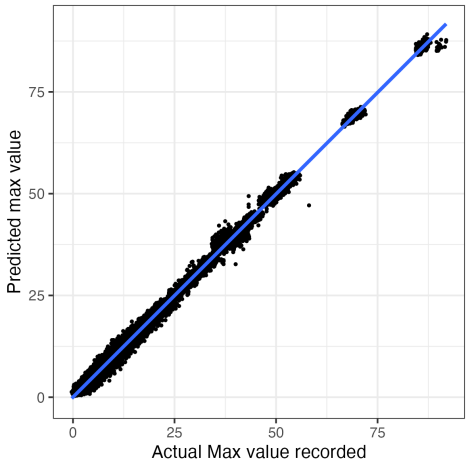
The water level data from IWM (Institute for Water Modelling) has data from 1951 to 2020 for 182 water level stations in Bangladesh. The left panel of figure B.1 shows the location of stations on a map. The data has the maximum and minimum water level recorded for each month, along with the geolocation of each station. I take a number of steps to clean the raw data. First, I remove anomalous observations based on large deviations from the mean for every station-month-year combination. This removed 749 observations out of around 116700. Second, I remove all observations for 5 specific stations whose observations were out of sync with the surrounding stations for extended periods of time.[1] This leaves 177 stations with 115938 station-year-month level observations.

[1]This can happen because a cyclone or flood shock can affect the equipment used to measure the water level, leading to wrong observations being recorded, or due to human error in reading the correct water level.

Figure B.1: Station map and interpolation



(a) Map of water level stations



(b) Predicted vs actual water level of stations (meters above sea level)

There are gaps in the water level records of these stations: with no gaps, there should be 148680 ($177 \times 12 \times 70$) observations between January 1951 to December 2020, which implies close to 33000 missing observations.[2] To impute missing values, I use the spatiotemporal relationship between stations. For each station-month-year observation, 5 nearby stations are selected that (i) have data for the particular year-month and (ii) also have data in other years for the same month when the station in question also has data. This allows me to use the relationship between the station in question and the 5 selected stations in other years of the same months to predict what the water level would have been in the current-year month. I do this for all observations, irrespective of whether the data is missing or not, as long as the panel to run the linear regression has at least 15 observations. The right panel of figure B.1 shows the relationship between the predicted maximum water level and the observed maximum water level for observations where data is not missing. The figure suggests that this method is reliable in filling missing observations.

To avoid mixing predicted and actual observations, only the predicted water level observations are used to construct flooding. I then transform these station-year-month records into upazila-year-month level using the following steps:

1. For each month, a water surface image is created by interpolating maximum water levels using inverse distance weighting onto a grid defined at 2-decimal precision in latitude and

[2]There are more observations missing in the 1951-1970 period, which is promising as I mainly use data from 1971 onwards to construct the flood shock for the empirical exercise.

longitude (approximately 1.11×1.11 km). Each grid cell uses data from the four nearest stations for interpolation.

2. The level of rainfall, data for which is also available at a grid defined at 2 decimal places, is added to the interpolated water surface level for each month.

3. Elevation for the grid cell is subtracted from the sum of steps 1 and 2.[3]

4. Steps 1–3 are repeated for each month from 1951–2020, producing monthly flood maps at the grid level.

5. For each upazila, I average flooding across its grid points, setting negative values to zero. This yields an upazila–year–month level flood measure in meters.

The left panel of figure B.2 shows the flood map for August 2017, which was one of the biggest floods in recent years. The map assigns a value of 1 to upazilas which had more than 0.5 meters of flooding. The map aligns well with the actual flood maps constructed at the time by the Flood Forecasting and Warning Circle (FFWC) of Bangladesh (see figure 1 here).

B.1.2 Construction of cyclone shocks

To construct upazila-year-month level cyclone shocks, I use the Cyclonic Storms landfalls database of the World Bank. The database has information on the path of each cyclone, maximum windspeed and maximum radius that affected any part of Bangladesh between 1960 and 2020. While I use the information on cyclone path and radius from this database, there seems to be coding errors for information on windspeed. For example, a large number of cyclones are assigned a windspeed of either 35 or 65 knots. I instead use the windspeed provided in databases of either JTWC (Joint Typhoon Warning Center) or BMD (Bangladesh Meteorological Department).

Using information on the path of the cyclone, the maximum windspeed and maximum radius, a map is created for each cyclone, with the cyclone shock in terms of windspeed at the level of at a grid defined at 2 decimal places. This is done using the following steps:

1. I assume that each cyclone attains its maximum windspeed and radius at landfall, with both the windspeed and radius declining linearly along the path of the cyclone.

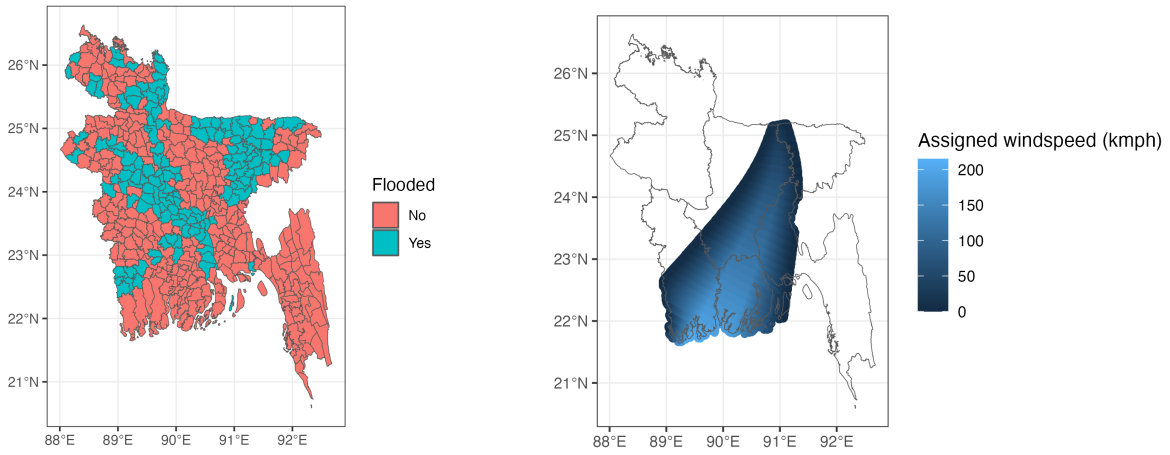
2. For each cyclone, I create an inner and outer zone. The inner zone is based on the radius in the Cyclonic Storms landfalls database. The outer zone is created based on the maximum windspeed, with a cyclone with a higher windspeed having a larger outer zone. Within the

[3] In addition, a correction of 0.46 m (1.5 ft) is applied, as the water level stations are located 0.46 m below mean sea level. For more information, see here.

outer zone, the assigned windspeed goes from 100% of the inner zone to 0% inner zone as distance from the eye of the cyclone increases.

The right panel of figure B.2 shows the constructed map of cyclone Sidr that hit Bangladesh in November 2007. There are two features to note about the map that shed light on the construction of the cyclone shock. First, the the assigned windspeed and radius of the cyclone decreases as the cyclone progresses on land. Second, the inner and outer zones are clearly visible, with inner zones having a much higher assigned windspeed. I convert grid level data on cyclone windspeed to upazila-year-month level by taking average over grids within each upazila.

Figure B.2: Maps showing construction of flood and cyclone shocks



(a) Flood map of Aug 2017

(b) Map of cyclone Sidr: Nov, 2007

B.1.3 Implementation of the Fast Marching Method to calculate trade costs

To calculate trade costs between upazilas, I implement the Fast Marching Method (FMM) on a road network map of Bangladesh.[4] Primary roads (i.e. highways) are assigned a travel speed of 48 miles per hours, secondary roads (i.e. all other roads) are assigned 24 miles per hour, waterways 3 miles per hour and anywhere else on the map is assigned 2 miles per hour. I build on the code in Allen and Arkolakis [2014] on how to implement the FMM. The procedure gives the travel time (in hours) between any bilateral pairs of upazilas in Bangladesh.

The functional form used to convert travel time (in hours) to trade costs is $\tau_{un} = \delta_0(\text{travel time})^{\delta_1}$ and the calibrated values of $\delta_0 = 1.63$ and $\delta_1 = 0.076$ are taken from Pellegrina [2022]. Additionally, trade costs within the upazila are set to be 1, so $\tau_{un} = 1$ if $u = n$.

[4]The map used can be found here.

B.2 Additional tables and regressions

Table B.1: Summary statistics (Agricultural census data)

Variable	1984	1996	2008
Land Share Irrigated	0.20	0.46	0.63
Average Landholding Size (in Acres)	2.01	1.52	1.26
Cropping Intensity	1.62	1.60	1.61
Share Aman Rice	0.59	0.59	0.49
Share Boro Rice	0.16	0.34	0.42
Share Wheat	0.07	0.08	0.03
Average Flood Level (m, previous 12 years)	0.29	0.31	0.34
Average Cyclone Windspeed (km/h, previous 12 years)	2.41	4.18	4.96

Table B.2: Summary statistics (Population census data)

Variable	1981	1991	2001	2011
Population density (persons per acre)	2.51	3.06	3.58	4.15
Average household size	5.78	5.48	4.89	4.48
Agricultural employment share	0.61	0.55	0.53	0.47
Non-agricultural employment share	0.39	0.45	0.47	0.53
Average flood level (m, previous 10 years)	0.30	0.32	0.33	0.31
Average cyclone windspeed (km/h, previous 10 years)	2.45	2.63	5.76	3.87

Table B.3: Cropping seasons for the six main crops

Crop	Growing + Harvesting season
Aus rice	Mid March to June
Aman rice	End June to Mid November
Boro rice	Mid November to Mid April
Wheat	Mid November to March
Jute	Mid March to June
Potato	Mid September to Mid February

Table B.4: Crop choice and climate shocks (first differences)

Dependent Variable:	Δ_{12} Land share for crop in Net cultivated area			
	(1)	(2)	(3)	(4)
Δ_{12} flooding level (m)	-0.435***	-0.405***	-0.530***	-0.508***
	(0.090)	(0.089)	(0.088)	(0.088)
Δ_{12} cyclone windspeed (100 kmph)	-0.159*	-0.059	-0.182**	-0.052
	(0.082)	(0.072)	(0.084)	(0.071)
Δ_{12}flooding level out season (m)			0.358***	0.340***
			(0.075)	(0.080)
Δ_{12} cyclone windspeed out season (100 kmph)			-0.122	-0.006
			(0.075)	(0.054)
Division-year FE	Yes	No	Yes	No
Crop type-year FE	Yes	Yes	Yes	Yes
Observations	4,510	4,510	4,510	4,510

Note: The panel includes years 1984, 1996 and 2008. Standard errors clustered at the upazila level in parentheses. Only those upazilas that had non-missing observations for all three years have been included. Observations are weighted by the lag of the area of the crop in the upazila. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.5: Crop choice and climate shocks (Other crops)

Dependent Variable:	Share of other crops in gross cropped area	
	(1)	(2)
flooding level (m)	-0.176***	-0.172***
	(0.057)	(0.056)
cyclone windspeed (100 km/h)	0.076	0.197***
	(0.080)	(0.071)
Division-year FE	Yes	No
Upazila FE	Yes	Yes
Year FE	No	Yes
Observations	1,353	1,353

Note: The panel includes years 1984, 1996 and 2008. Standard errors clustered at the upazila level in parentheses. Only upazilas with non-missing observations across all three years are included. Observations are weighted by average net cultivated area across the three census years. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table B.6: Crop choice and climate shocks (binary shocks)

Dependent Variable:	Land share for crop in Net cultivated area			
	(1)	(2)	(3)	(4)
flooding binary	-0.271***	-0.260***	-0.282***	-0.276***
	(0.051)	(0.052)	(0.052)	(0.054)
cyclone binary	-0.127	-0.328***	-0.057	-0.151
	(0.100)	(0.115)	(0.098)	(0.106)
flooding binary out season			0.178***	0.170***
			(0.052)	(0.052)
cyclone binary out season			-0.422***	-0.586***
			(0.093)	(0.108)
Division-year FE	Yes	No	Yes	No
Upazila-crop FE	Yes	Yes	Yes	Yes
Crop type-year FE	Yes	Yes	Yes	Yes
Observations	6,765	6,765	6,765	6,765

Note: The panel includes years 1984, 1996 and 2008. Standard errors clustered at the upazila-year level in parentheses. Only those upazilas that had non-missing observations for all three years have been included. Observations are weighted by the average Net cultivated area of the crop in the upazila across the three census years. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.7: Crop choice and climate shocks (All crops individually)

Dep. variable:	Land share in net cultivated area				
	Aus rice	Aman rice	Boro rice	Wheat	Jute
	(1)	(2)	(3)	(4)	(5)
flooding level (m)	0.039	-0.318***	-0.968**	-0.499	0.183
	(0.157)	(0.108)	(0.453)	(0.347)	(0.170)
cyclone windspeed (100 km/h)	0.040	-1.242***	0.456*	-0.171	-0.148
	(0.204)	(0.252)	(0.244)	(0.329)	(0.134)
Division-year FE	Yes	Yes	Yes	Yes	Yes
Upazila FE	Yes	Yes	Yes	Yes	Yes
Observations	1,353	1,353	1,353	1,353	1,353

Note: The panel includes years 1984, 1996 and 2008. Standard errors are clustered at the upazila level in parentheses. Only upazilas with non-missing observations for all three years are included. Observations are weighted by the average crop area in the upazila across the three census years. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table B.8: Sectoral employment and climate shocks (first differences)

Dependent Variable:	Δ_{10} Agricultural employment share			
	(1)	(2)	(3)	(4)
Δ_{10} flooding level (m)	0.010	0.001		
	(0.032)	(0.031)		
Δ_{10} cyclone windspeed (100 km/h)	-0.046**	-0.047**		
	(0.022)	(0.022)		
Δ_{10} flooding binary			-0.011	-0.013
			(0.018)	(0.017)
Δ_{10} cyclone binary			-0.060**	-0.063**
			(0.025)	(0.024)
Division FE	Yes	No	Yes	No
Year FE	Yes	Yes	Yes	Yes
Observations	1,353	1,353	1,353	1,353

Note: The panel includes years 1981, 1991, 2001 and 2011. Standard errors are clustered at the upazila level in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table B.9: Sectoral employment and climate shocks (log of LHS)

Dependent Variable:	log(Agricultural employment share)			
	(1)	(2)	(3)	(4)
flooding level (m)	0.122	0.121*		
	(0.082)	(0.069)		
cyclone windspeed (100 km/h)	-0.207**	-0.090		
	(0.096)	(0.080)		
flooding binary			-0.002	0.017
			(0.044)	(0.042)
cyclone binary			-0.255***	-0.167**
			(0.085)	(0.073)
Division-year FE	Yes	No	Yes	No
Upazila FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes
Observations	1,804	1,804	1,804	1,804

Note: The panel includes years 1981, 1991, 2001 and 2011. Standard errors are clustered at the upazila level in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table B.10: Cropping intensity and climate shocks

Dependent Variable:	Cropping intensity			
	(1)	(2)	(3)	(4)
flooding level (m)	-0.097	-0.160		
	(0.134)	(0.110)		
cyclone windspeed (100 km/h)	-1.756***	-1.431***		
	(0.257)	(0.231)		
flooding binary			-0.012	-0.029
			(0.067)	(0.076)
cyclone binary			-1.328***	-1.646***
			(0.242)	(0.236)
Division-year FE	Yes	No	Yes	No
Upazila FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes
Observations	1,353	1,353	1,353	1,353

Note: The panel includes years 1984, 1996 and 2008. Standard errors are clustered at the upazila level in parentheses. Only upazilas with non-missing observations for all three years are included. Observations are weighted by average net cultivated area of the upazila across the three census years. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table B.11: Net cultivated area and climate shocks

Dependent Variable:	log(Net cultivated area)			
	(1)	(2)	(3)	(4)
flooding level (m)	-0.024	-0.166		
	(0.110)	(0.113)		
cyclone windspeed (100 km/h)	-0.494***	-0.446***		
	(0.164)	(0.140)		
flooding binary			-0.063	-0.094*
			(0.052)	(0.054)
cyclone binary			-0.545**	-0.479**
			(0.237)	(0.208)
Division-year FE	Yes	No	Yes	No
Upazila FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes
Observations	1,353	1,353	1,353	1,353

Note: The panel includes years 1984, 1996 and 2008. Standard errors are clustered at the upazila level in parentheses. Only upazilas with non-missing observations across all three years are included. Observations are weighted by average net cultivated area of the upazila across the three census years. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table B.12: Crop choice and climate shocks (Dividing 12 year period)

Dependent Variable:	Land share for crop in net cultivated area				
	(1)	(2)	(3)	(4)	(5)
flooding_level_prev9to12	-0.205***			-0.176***	-0.211***
	(0.046)			(0.046)	(0.050)
cyclone_windspeed_prev9to12	0.054			0.041	0.023
	(0.071)			(0.074)	(0.072)
flooding_level_prev5to8		-0.180***		-0.116*	-0.109*
		(0.061)		(0.064)	(0.060)
cyclone_windspeed_prev5to8		-0.179***		-0.164***	-0.150***
		(0.047)		(0.046)	(0.047)
flooding_level_prev4			-0.694***		-0.716***
			(0.082)		(0.080)
cyclone_windspeed_prev4			-0.051		-0.016
			(0.065)		(0.068)
Division-year FE	Yes	Yes	Yes	Yes	Yes
Upazila-crop FE	Yes	Yes	Yes	Yes	Yes
Crop type-year FE	Yes	Yes	Yes	Yes	Yes
Observations	6,765	6,765	6,765	6,765	6,765

Note: The panel includes years 1984, 1996 and 2008. Standard errors are clustered at the upazila-year level in parentheses. Only upazilas with non-missing observations across all three years are included. Observations are weighted by average crop area in the upazila across the three census years. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table B.13: Value of adaptation (exponential damage function)

	Intensity of the shock		
	$1.5\times$ 2000's avg	$2\times$ 2000's avg	$2.5\times$ 2000's avg
Uncorrelated shocks	13.9%	22.3%	28%
Correlated at upazila level	11.5%	18.6%	23.4%
Correlated shocks	9.5%	16.3%	21.4%

Table B.14: Value of adaptation with migration (exponential damage function)

	Intensity of the shock		
	$1.5\times$ 2000's avg	$2\times$ 2000's avg	$2.5\times$ 2000's avg
Uncorrelated shocks	22.4%	30.6%	36.2%
Correlated at upazila level	20.3%	27.3%	32.2%
Correlated shocks	18.6%	25.3%	30.1%

Table B.15: Value of adaptation (logistic damage function, $\theta = 2$)

	Intensity of the shock		
	$1.5\times$ 2000's avg	$2\times$ 2000's avg	$2.5\times$ 2000's avg
Uncorrelated shocks	20.3%	32.4%	40.3%
Correlated at upazila level	18%	28.4%	35.1%
Correlated shocks	14.8%	25.5%	33.3%

Table B.16: Value of adaptation (logistic damage function, $\theta = 4$)

	Intensity of the shock		
	$1.5\times$ 2000's avg	$2\times$ 2000's avg	$2.5\times$ 2000's avg
Uncorrelated shocks	25.4%	40.6%	50.7%
Correlated at upazila level	21.3%	34.1%	42.5%
Correlated shocks	18.1%	31.2%	40.8%

B.3 Additional figures

Figure B.3: Upazila level distribution of flood shocks (prev 12 years)

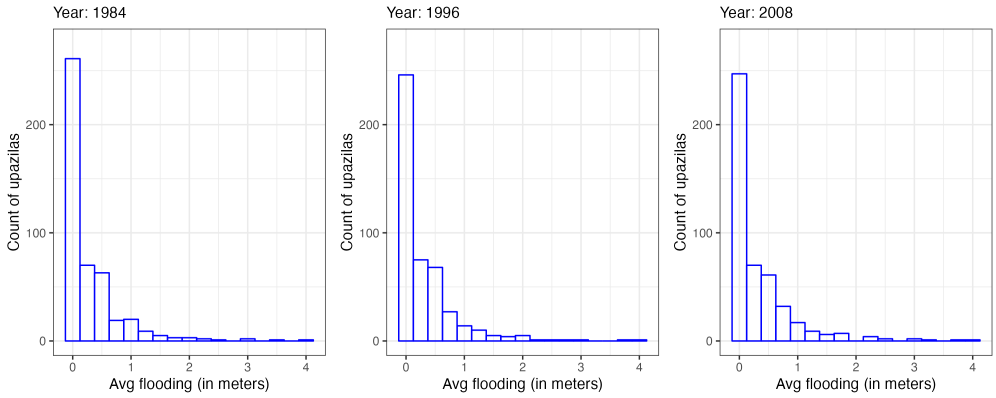


Figure B.4: Upazila level distribution of cyclone shocks (prev 12 years)

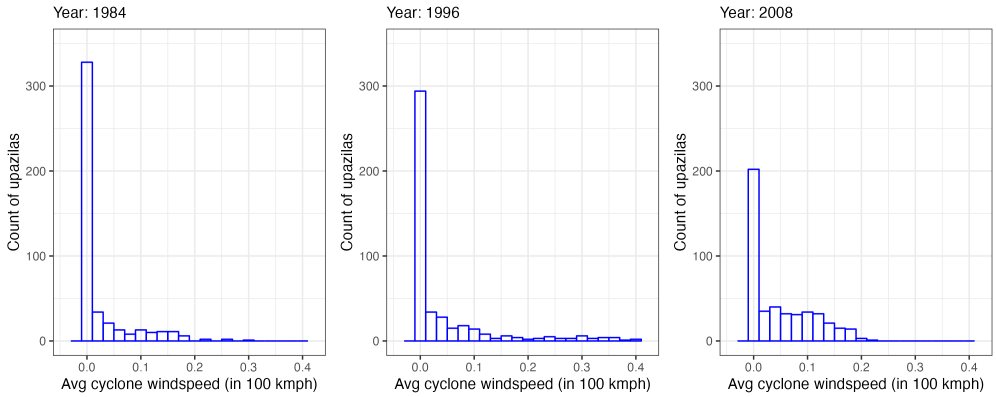


Figure B.5: Month wise flood and cyclone propensity (1960-2010)

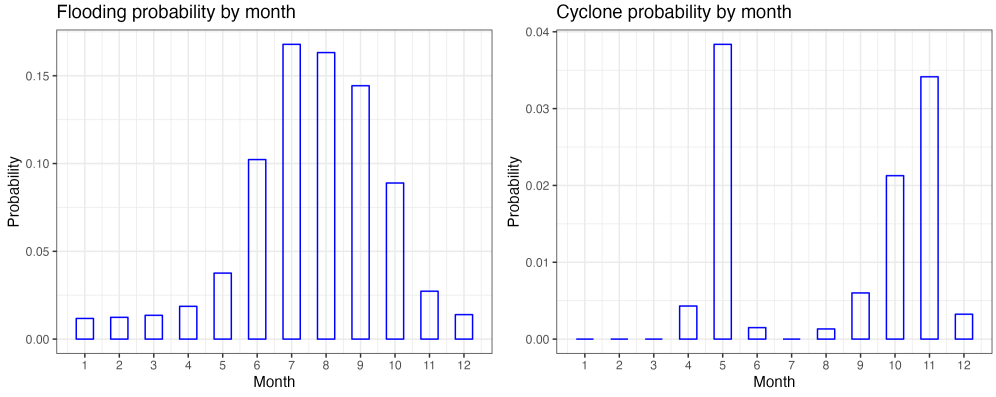


Figure B.6: Crop shares and calibrated productivities

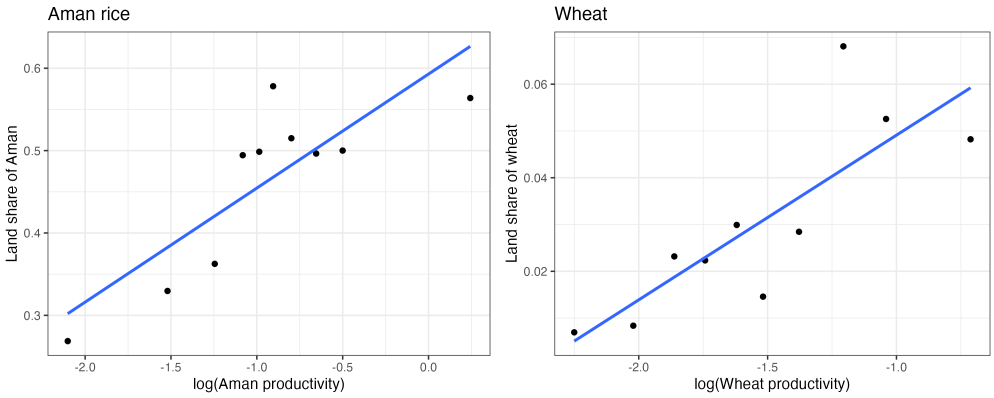
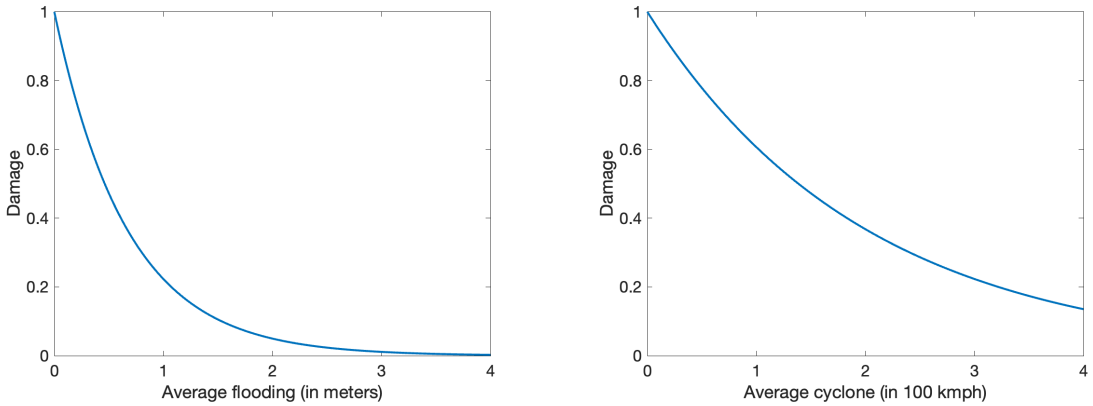


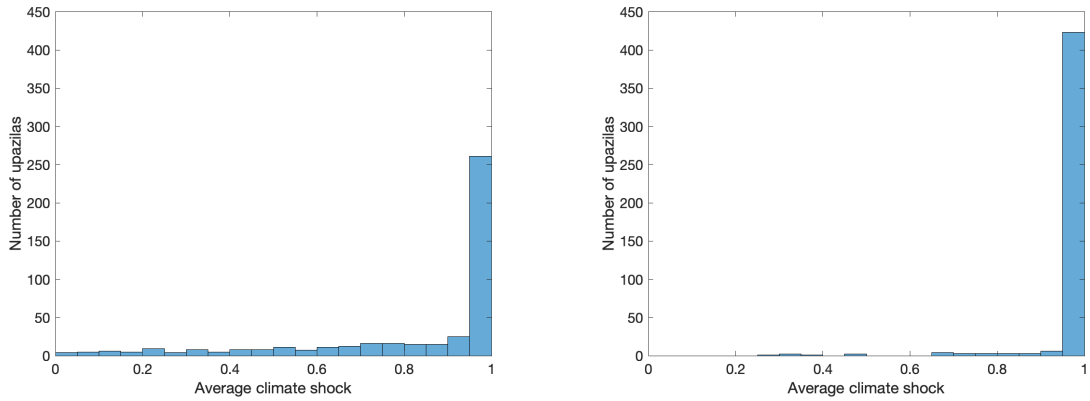
Figure B.7: Calibrated damage functions (exponential parameterization)



(a) Flooding

(b) Cyclones

Figure B.8: Calibrated μ_{uc} with logistic damage function (2001-2010)



(a) Aman rice (b) Wheat

B.4 Model Extensions and additional derivations

B.4.1 Model with migration

In this section, I add migration to the model of section 2.4. Location preferences are added to the utility function, which will now look like the following:

$$U_{iu} = \varepsilon_{iu} C_{u,A}^{\alpha} C_{u,M}^{1-\alpha}$$

Apart from consumption of agriculture and non-agriculture composite, the utility for individual i from living in upazila u also depends on the idiosyncratic preference shock ε_{iu}. Individuals will draw preference shocks ε_{iu} across locations and choose to live in a location that offers the highest utility. The preference shocks will be drawn from the following distribution: $F_{u,c}(\varepsilon) = Pr[\varepsilon_{iu} \leq \varepsilon] = e^{-\left(\varepsilon\right)^{-\lambda}}$

λ, represents the dispersion of preference draws across workers in each location. A higher λ implies lower dispersion of shocks, which would make migration more responses to differences in real wages. In such a model, the share of workers that live in each location, using the properties of the Frechet distribution, will be given by

$$\frac{L_u}{\bar{L}} = \frac{(\frac{w_u}{P_u})^{\lambda}}{\sum_u (\frac{w_u}{P_u})^{\lambda}} \tag{B.1}$$

Note that migration is based on real wages in equation B.1, and not total income per capita. Land rents accrue to landlords who are immobile. Based on equation B.1, a higher real wage would incentivize a bigger share of workers to live in the upazila. The object that will be equalized

across locations in equilibrium is the expected utility given by

$$\bar{W} = \Gamma(1 - \frac{1}{\lambda})\Big(\sum_{u}(\frac{w_u}{P_u})^{\lambda}\Big)^{1/\lambda} \tag{B.2}$$

Equilibrium of the model with migration is similar to the equilibrium in section 2.4.7, with the additional equation that the total labor in each location $\{L_u\}_{\forall u}$ determined in equilibrium and pinned down by equation B.1.

B.4.2 Counterfactuals with fixed crop and sectoral employment shares

This sections contains equations necessary to solve the counterfactual model where crop, sectoral employment shares and labor in each upazila are not allowed to adjust and are fixed at the baseline equilibrium. In a world where total population, crop shares and the number of workers in each sectors is fixed, the return for a plot of land i growing crop c in upazila u is given by

$$\frac{p_{uc}\mu_{uc}}{p_{uc,bs}\mu_{uc,bs}} p_{uc,bs}\mu_{uc,bs}(A_{iuc}K_{iu})^{\gamma_c} l_{iuc}^{1-\gamma_c} - \frac{w_u}{w_{u,bs}} w_{u,bs} l_{iuc} = r_{iuc}K_{iu}$$

where the subscript bs represents the value in the baseline equilibrium. Note that because we are fixing the number of workers in each sector/crop, the amount of labor used in each plot will still be given by the FOC of the baseline equilibrium in equation 2.5 and $l_{iuc} = l_{iuc,bs}$. We can boil down the above equation to the following

$$\Big(\frac{1-\gamma_c}{w_{u,bs}}\Big)^{\frac{1-\gamma_c}{\gamma_c}} (\mu_{uc,bs}p_{uc,bs})^{1/\gamma_c} A_{iuc}\Big[\frac{p_{uc}\mu_{uc}}{p_{uc,bs}\mu_{uc,bs}} - \frac{w_u}{w_{u,bs}}(1-\gamma_c)\Big] = r_{iuc} \tag{B.3}$$

Equation B.3 gives the return per unit of land in an economy where adaptation is not allowed. The total rents from all plots growing crop c in upazila u will be given by

$$\begin{aligned}
r_{uc} &= \pi_{uc,bs}K_u \int_{i\in A_{iuc}>A_{iuk}\forall k} \Big(\frac{1-\gamma_c}{w_{u,bs}}\Big)^{\frac{1-\gamma_c}{\gamma_c}} (\mu_{uc,bs}p_{uc,bs})^{1/\gamma_c}\Big[\frac{p_{uc}\mu_{uc}}{p_{uc,bs}\mu_{uc,bs}} - \frac{w_u}{w_{u,bs}}(1-\gamma_c)\Big] A_{iuc} \\
&= \Big(\frac{1-\gamma_c}{w_{u,bs}}\Big)^{\frac{1-\gamma_c}{\gamma_c}} (\mu_{uc,bs}p_{uc,bs})^{1/\gamma_c}\Big[\frac{p_{uc}\mu_{uc}}{p_{uc,bs}\mu_{uc,bs}} - \frac{w_u}{w_{u,bs}}(1-\gamma_c)\Big]\pi_{uc,bs}K_u \int_{i\in A_{iuc}>A_{iuk}\forall k} a g_{uc}(a)\, da \\
&= \Big[\frac{p_{uc}\mu_{uc}}{p_{uc,bs}\mu_{uc,bs}} - \frac{w_u}{w_{u,bs}}(1-\gamma_c)\Big]\pi_{uc,bs}K_u \frac{\Phi_{u,bs}}{\gamma_c}\Gamma\left(1-\frac{1}{\theta}\right).
\end{aligned}$$

The same solution for the distribution as in equation 2.10 is used above as the plots that actually grow crop c stays the same as in the baseline equilibrium. This implies that the summary statistic $\Phi_{u,bs}$ from the baseline equilibrium will be used to solve for the no adaptation equilibrium.

With no adaptation, total labor demand for a given crop c stays the same as in the baseline

equilibrium at $l_{uc,bs} \forall c$. With labor used fixed in each crop/sector at the number of workers in the baseline equilibrium, total labor used in the manufacturing sector will be given by $l_{uM,bs}$ and total revenues from them manufacturing sector will be given by $p_{uM} A_{uM} l_{uM,bs}$. Total income in the upazila is given by

$$Y_u = w_u L_u + \sum r_{uc}$$

The market clearing conditions in equation 2.14 will still continue to apply, and labor market clearing in equation 2.13 will hold by design as labor use is fixed across sectors. Under the counterfactuals where no adaptation is allowed, equilibrium will involve finding prices and wages, given the allocations, prices and wages of the baseline equilibrium.

APPENDIX C

Appendix to Chapter 3

C.1 More Details on the Background

Prior to 2010, the Senkaku Islands (Diaoyu in China) were already a longstanding source of tension in Sino-Japanese relations. Japan incorporated the islands into Okinawa Prefecture in January 1895 and administered them until 1945; the United States governed Okinawa, including the Senkaku islands, from 1945 until returning them to Japan under the Okinawa Reversion Agreement on May 15, 1972. China has asserted historical sovereignty based on Qing-era records, and tensions first emerged in the 1970s after a 1969 UN survey indicated potential oil and gas resources in the area.

On the morning of September 7, 2010, the Chinese trawler, Minjinyu 5179, entered waters claimed by Japan near the Senkaku islands and ignored orders from the Japan Coast Guard vessels, Yonakuni and Mizuki. After two collisions, the Coast Guard boarded the trawler and arrested Captain Zhan Qixiong on charges of obstructing official duties and illegal fishing. The Chinese government demanded his unconditional release and suspended diplomatic meetings with Tokyo. He was held for 17 days and released without trial on September 24; Japan cited diplomatic and political considerations in its decision. During the period from September 7 to September 13, the Chinese government lodged six formal protests, summoning Japan's ambassador and demanding Zhan's immediate release.

Although no formal embargo on Japan alone was declared, China's sharp cuts to its 2010 rare-earth export quota took effect within weeks of the Senkaku/Diaoyu clash. Beginning in October 2010, China's customs authorities reduced the 2010 rare-earth export quota by more than 70 percent year-on-year in the fourth quarter; the government justified these cuts on environmental conservation grounds, while exempting domestic users from similar restrictions. Global rare earth prices rose more than tenfold.

In March 2012, Japan, the United States, and the European Union jointly requested WTO consultations against China's export restrictions on rare earths (DS431, DS432, and DS433). After consultations proved inconclusive, the complainants requested a panel on July 23, 2012. The panel

report issued on March 26, 2014 (WT/DS431/R) concluded that China's measures violated GATT Articles I and XI as well as China's WTO accession commitments. It rejected China's Article XX(g) conservation defense on the grounds that domestic consumers were not similarly restricted. The Appellate Body affirmed these findings on August 7, 2014 (WT/DS431/AB/R), and China phased out its export quotas by mid-2015.

C.2 Additional Tables and Figures

Table C.1: Critical Mineral 8-digit HS Codes

Critical minerals	Treated/control	8 digit HS codes							
Rare earth	Treated	2846.90.20	2846.90.40	2846.90.80	2805.30.00	2846.10.00	3606.90.30	2612.20.00	
Tungsten		2611.00.30	2611.00.60	2620.99.10	2849.90.20	2825.90.30	2827.39.40	2849.90.30	2850.00.10
Molybdenum		2613.10.00	2613.90.00	2825.70.00	3815.90.20	3824.99.34			
Cobalt		2605.00.00	2822.00.00	2827.39.60	2833.29.10	2836.99.10	2915.29.30		
Nickel	Control	2604.00.00	2825.40.00	2827.35.00	2833.24.00	3815.11.00	3824.99.39		
Graphite		2504.10.10	2504.10.50	2504.90.00	3801.10.10	3801.10.50	3801.20.00	3801.30.00	3801.90.00
Copper		2603.00.00	2825.50.10	2825.50.20	2825.50.30	2827.41.00	2833.25.00	2827.60.10	2853.90.10
Lithium		2805.19.90	2825.20.00	2836.91.00	2845.30.00	2826.90.90	2904.33.00		

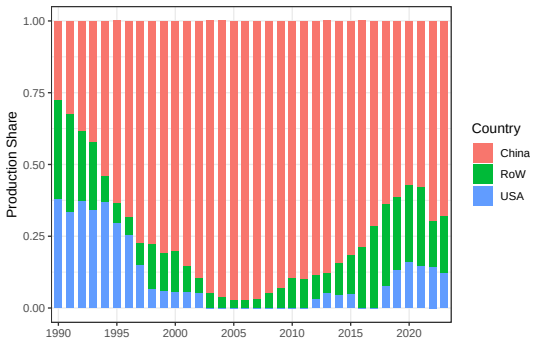
Note: This table presents the 8-digit HS codes we use to identify US firms importing particular critical minerals.

Table C.2: Selected Industrial Uses of Treated and Control Group Critical Minerals

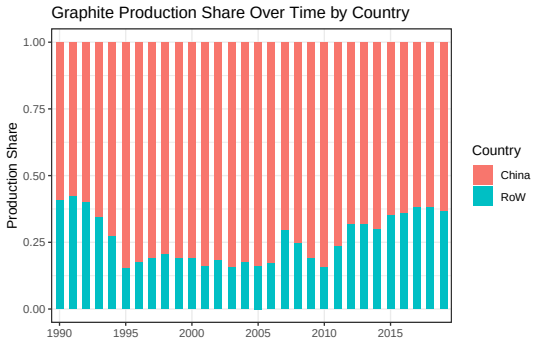
Critical minerals	Industrial use
Rare Earths	Catalysts (petroleum refining, automotive), permanent magnets (EV motors, wind turbines), ceramics and glass, polishing materials
Tungsten	Carbide tooling (construction, mining, drilling), alloys and specialty steels, electrical components (electrodes, filaments), chemical catalysts
Nickel	Stainless steel (65%), superalloys (aerospace, turbines), electroplating, chemical catalysts
Copper	Electrical wiring and power cables, construction (plumbing, roofing), industrial machinery, brass and bronze alloys
Cobalt	Superalloys (aircraft engines), battery cathodes (Li-ion batteries), chemical catalysts, carbide tools
Molybdenum	Alloying agent (structural steels, superalloys), chemical catalysts (lubricants, pigments), high-temperature refractories
Lithium	Rechargeable batteries (EV, electronics), ceramics and glass flux, lubricating greases, metallurgical fluxes (aluminum casting)
Graphite	Battery anodes, fuel cells, high-temperature lubricants, brake linings, refractories, steelmaking electrodes

Note: This table reports industrial uses of treated and control group critical minerals. The information is obtained from U.S. Geological Survey [2024].

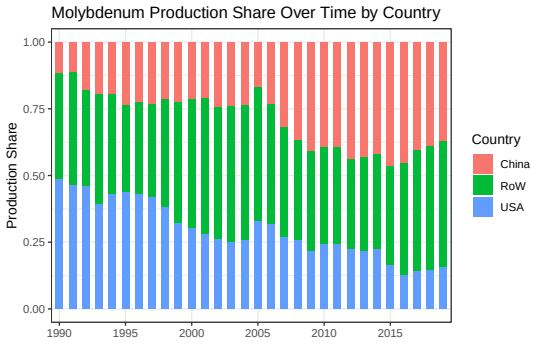
Figure C.1: Global Production Shares of Critical Minerals by China, US, and Rest of the World



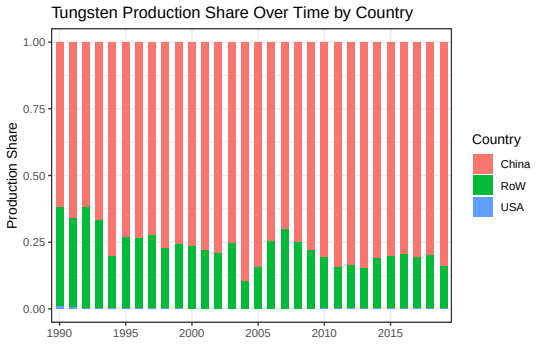
(a) Rare earth



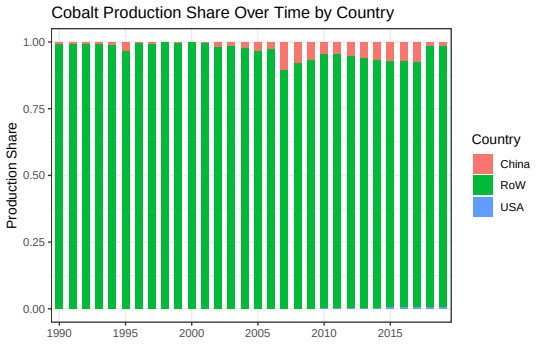
(b) Graphite



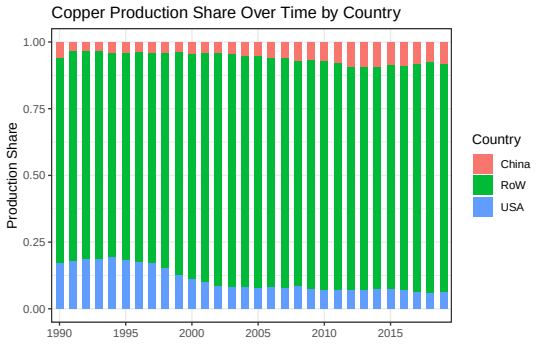
(c) Molybdenum



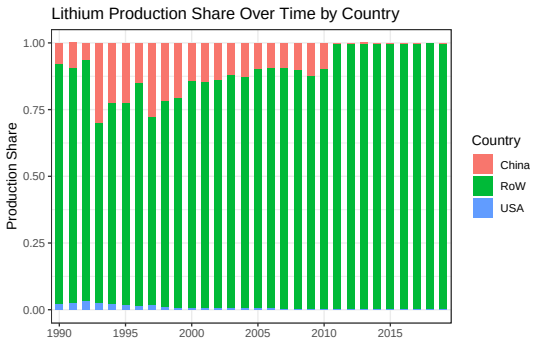
(d) Tungsten



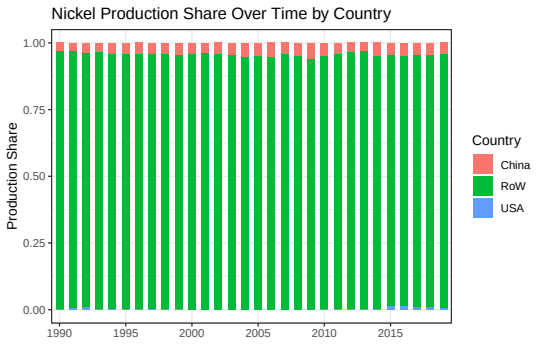
(e) Cobalt



(f) Copper

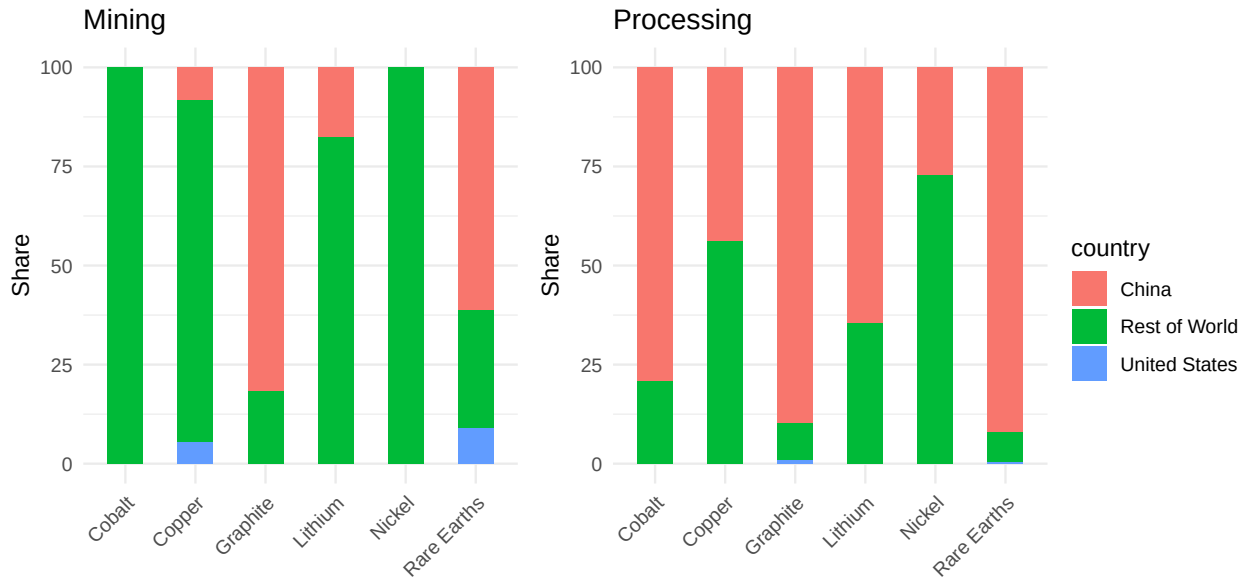


(g) Lithium



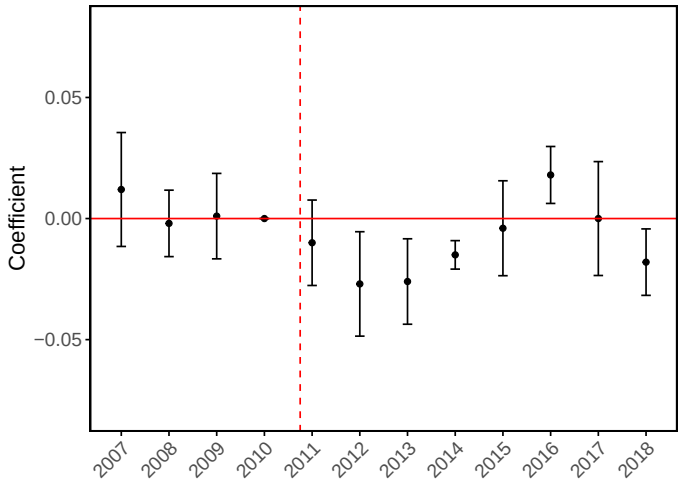
(h) Nickel

Figure C.2: China's Dominance in Mining and Process Capacity of Selected Critical Minerals in 2023



Note: This table reports global market concentration by countries for mining and processing industries of selected critical minerals in 2023. The information is obtained from International Energy Agency [2023].

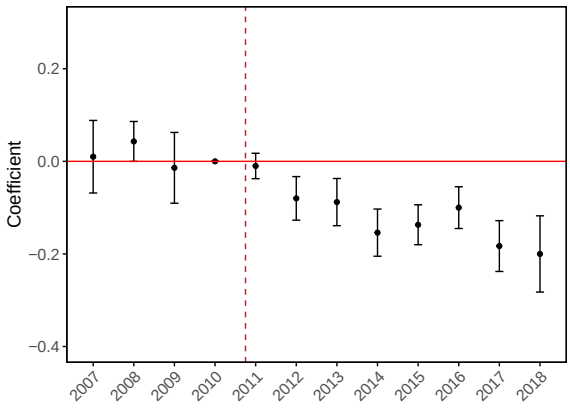
Figure C.3: The Effects of the 2010 China's Quota on US Rare Earth Importers' Export Status Dummy



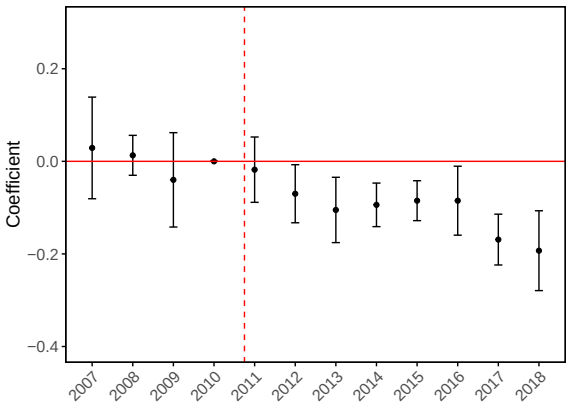
Dep var. Export dummy

Note: This figure reports the estimated coefficients of equation (3.1). The 95% confidence intervals, based on standard errors clustered at the NAICS 4-digit levels, are reported. The 2010 coefficient β^0 is normalized to zero. All specifications include firm and NAICS 2-digit-year fixed effects.

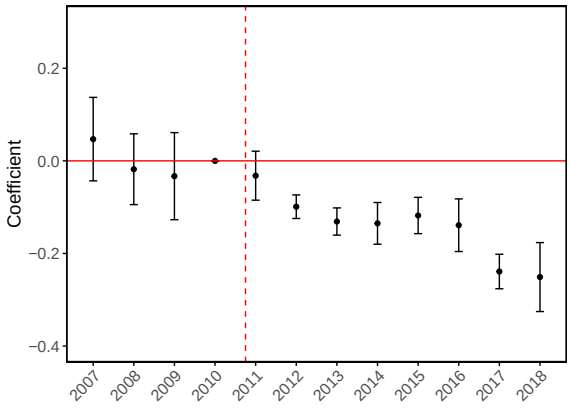
Figure C.4: Unique Products Exported by Category



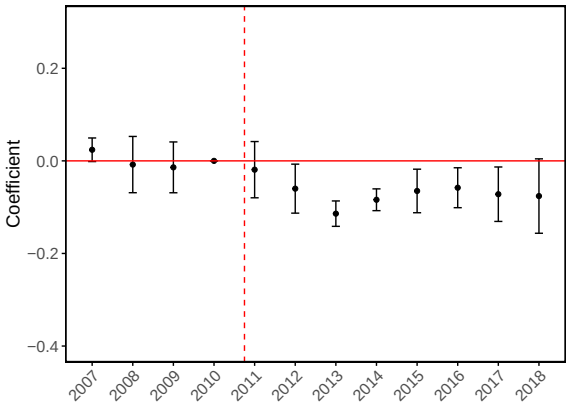
(a) Electrical equipment



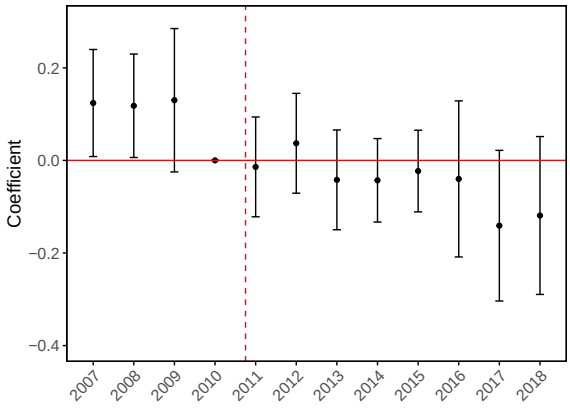
(b) Machinery



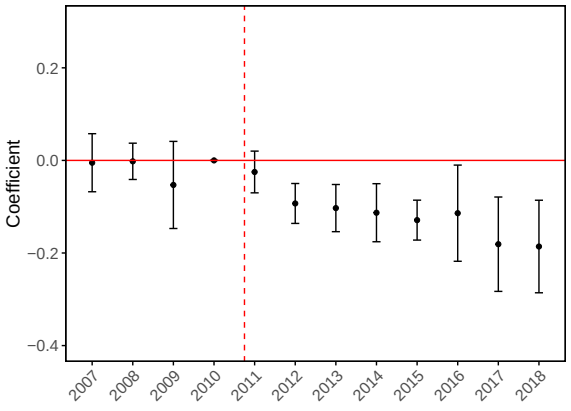
(c) Metals



(d) Mineral products and chemicals



(e) Transportation equip.



(f) Other products

C.3 Simple Theory

In this section, we develop a simple model that rationalizes our findings. There is a unit mass of entrepreneurs and a unit mass of workers. Each entrepreneur owns firm and earns income from its firm's profit. Workers supply labor inelastically and earn wages. We normalize domestic price level to one, so profits or labor income are in real terms.

An entrepreneur is risk-averse with a concave utility function $U(\cdot)$: $U'(\cdot) > 0$ and $U''(\cdot) < 0$. Their indirect utility function can be approximated as[1]:

$$V(\pi) \approx E[\pi] - \frac{\kappa}{2}\text{Var}[\pi], \qquad \kappa \equiv -U''(E[\pi])/U'(E[\phi]) \tag{C.1}$$

where π is their total profit and Var$[\pi]$ is variance of profits.

Geopolitical risk is modeled as uncertainty associated with import costs of rare earth minerals.

Each entrepreneurs have their main product and sub-product. Their main product can be produced without fixed costs in both domestic and foreign markets (or it can be considered as if they already paid for it) and generates the highest profit. However, because production for main product requires labor and imported rare earth minerals, their profit is stochastic. Sub-products can be produced after incurring fixed costs.

Each entrepreneur is endowed with a limited unit mass of entrepreneurial resources (e.g. time). They can use these resources to either diversity geopolitical risks associated with main product or improving quality of sub products.

Profits of main products are given as

$$\pi^m = \frac{1}{\eta}\Big(\frac{\mu w^\alpha c^{1-\alpha}}{a}\Big)^{1-\eta}(D_d + D_x) \tag{C.2}$$

where η is the elasticity of substitution and $\mu \equiv \frac{\eta}{\eta-1}$ is constant markup charged by firms. Firms produce their main products using labor and rare earth material from China, with Cobb Douglas share α, which gives unit costs of input bundle of $w^\alpha c^{1-\alpha}$, where c is import costs of rare earth (inclusive of trade costs). Firms take w and c as given. D_d is domestic market size and D_x is foreign market size (inclusive of trade costs), which they also take as given.

π^m is possibly stochastic due to c, with a pdf of f. We denote the mean and variance of π associated with f as $E_f[\pi]$ and Var$_f[\pi]$.

Entrepreneurs can invest their entrepreneur resources to decrease risks associated with c.

[1]Note that the second-order Taylor approximation of the utility function around $E[\pi]$ gives $E[U(\pi)] \approx U(E[\pi]) + \frac{1}{2}U''(E[\pi])\text{Var}[\pi]$. The certainty equivalent $\mathcal{E}$ gives the same utility with the expected utility: $E[U(\pi)] = U(E[\pi] - \mathcal{E}) \approx U(E[\pi]) - \mathcal{E}U'(E[\pi])$, where the first equality comes from the definition of the certainty equivalent and the last approximation is obtained by applying a first-order approximation. Combining the above two equations gives $\mathcal{E} = -\frac{1}{2}\frac{U''}{U'}\text{Var}[\pi]$. Using that $E[U(\pi)] = U(E[\pi] - \frac{1}{2}\frac{U''}{U'}\text{Var}[\pi])$, we can derive the indirect utility function.

Specifically, if they invest $e \in [0,1]$ amounts of resources, they can change the distribution of possible realizations of c from f to g:

$$g(\pi; e) = (1 - \epsilon(e))f(\pi) + \epsilon(e)\delta(\pi - E_f[\pi]), \tag{C.3}$$

where $\delta(\cdot)$ is the Diract delta function at 0, so $\delta(\pi - E_f[\pi])$ puts mass 1 at $\pi = E[\pi]$. It is straightforward to check that $g(\pi; e)$ is mean-preserving but variance decreasing pdf with f: $E_{g(e)}[\pi] = E_f[\pi]$, but $\text{Var}_{g(e)}[\pi] < (1 - \epsilon(e))\text{Var}_f[\pi]$, Also, if more resources are invested, the variance can be even more decreasing: $\text{Var}_{g(e)}[\pi]$ is decreasing in e.

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