Pontifícia Universidade Católica
do Rio de Janeiro

Flavio Lyrio Carneiro

Essays on Trade Policy and Labor Market Effects of the China Trade Shock

Tese de Doutorado

Thesis presented to the Programa de Pós–graduação em Economia, do Departamento de Economia da PUC-Rio in partial fulfillment of the requirements for the degree of Doutor em Economia.

Advisor : Prof. Claudio Ferraz
Co-advisor: Prof. Gabriel Ulyssea

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To Isadora.

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Abstract

Lyrio Carneiro, Flavio; Ferraz, Claudio (Advisor); Ulyssea, Gabriel (Co-Advisor). **Essays on Trade Policy and Labor Market Effects of the China Trade Shock**. Rio de Janeiro, 2021. 204p. Tese de Doutorado – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

This thesis consists of three chapters, all of which focus on the rise of China as a quasi-natural experiment in order to assess the effects of foreign trade shocks on the political economy of trade policy and on the dynamics of labor markets and earnings inequality in Brazil. In the first chapter, we use evidence on the differential exposure across local labor markets to this China shock in order to estimate its effect on Brazilian labor markets outcomes, in particular on measures of income inequality. First, we find that the export demand shock has decreased wage inequality in the tradables sector, mostly through the between-firms component of wage dispersion, and provide evidence that this reduction seems driven by a change in wage-setting behavior of firms, and may be linked to a reduction in the wage premium of exporter firms. We then estimate a model based on Helpman et al. (2016), and explore sectoral differences in the foreign demand shock to run counterfactual exercises that support the hypothesis that this shock can explain part of the aggregate reduction in the exporter wage premium and in wage dispersion. In the second chapter, we develop a version of the dynamic trade model by Caliendo et al. (2019) in order to estimate the effects of the dual China shock on the sectoral dynamics of Brazilian employment. We show that both shocks lead to a contraction in most manufacturing sectors, and an expansion in most services sectors, but the general equilibrium effects of the shocks are modest, especially if compared to an alternative counterfactual in which Brazilian productivity in primary sectors increase. We then extend the model to include two types of labor, skilled and unskilled. Results also point to small distributional effects of the China shock, but consistent with reduced-form evidence obtained in Chapter 1. In the final chapter, we build a novel dataset on Brazilian trade associations' characteristics in order to investigate whether industries with higher capacity of political organization are able to obtain more protection from foreign competitors. We use variation in import penetration as a measure of the need for trade protection, and address endogeneity on this measure by using an instrumental variables strategy based on the China import shock. Evidence suggests that industries with larger employer unions are able to obtain more protection, particularly through non-automatic licensing; the estimates suggest that this effect is higher when import penetration increases

more intensely, which is interpreted as increased need for protective measures.

Keywords

International Trade; China; Labor markets; Inequality; General Equilibrium; Trade Policy; Political Economy; Special Interest Politics; Non-Automatic Licensing.

Resumo

Lyrio Carneiro, Flavio; Ferraz, Claudio; Ulyssea, Gabriel. **Ensaios sobre os Efeitos do Comércio com a China no Mercado de Trabalho e na Política Comercial**. Rio de Janeiro, 2021. 204p. Tese de Doutorado – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

Esta tese é composta por três capítulos que enfocam o crescimento da China como um experimento quasi-natural de forma a avaliar os efeitos de choques de comércio exterior sobre a economia política da política comercial e sobre a dinâmica do mercado de trabalho e desigualdade de salários no Brasil. No primeiro capítulo, utilizamos evidência sobre diferenciais de exposição a esse choque da China entre mercados de trabalho locais para estimar seu efeito em indicadores do mercado de trabalho brasileiro, em particular em medidas de desigualdade de rendimentos. Primeiro, encontramos que o choque de demanda por exportações diminuiu a desigualdade de salários no setor de bens comercializáveis, sobretudo por meio do componente entre firmas da dispersão salarial, e apresentamos evidências de que essa redução parece causada por uma mudança no comportamento das firmas, e pode estar relacionado com uma redução no prêmio salarial de firmas exportadoras. Em seguida, estimamos um modelo baseado em Helpman et al. (2016), e exploramos diferenças setoriais no choque de demanda externa para realizar exercícios contrafactuais que corroboram a hipótese de que esse choque pode explicar parte da redução agregada no prêmio salarial de firmas exportadoras e na dispersão de salários. No segundo capítulo, desenvolvemos uma versão do modelo dinâmico de Caliendo et al. (2019) de modo a estimar os efeitos do duplo choque da China na dinâmica setorial do emprego no Brasil. Mostramos que ambos os choques levam à contração da maioria dos setores de manufaturas, e expansão da maioria dos setores de serviços, mas os efeitos de equilíbrio geral dos choques são modestos, especialmente quando comparados a um contrafactual alternativo no qual a produtividade brasileira nos setores primários aumenta. Estendemos o modelo para incluir dois tipos de trabalho, de alta e baixa qualificação; resultados apontam para efeitos distributivos pequenos, mas consistentes com resultados em forma reduzida obtidos no primeiro capítulo. No capítulo final, construímos uma base de dados inédita sobre características de associações setoriais brasileiras, com o intuito de investigar se os setores com maior capacidade de organização política são capazes de obter maior proteção contra competidores estrangeiros. Usamos variação na penetração de importações como uma medida da necessidade de proteção comercial, e para lidar com a endogeneidade nessa medida usamos um instrumento baseado no choque de importações da China. A evidência sugere que setores com maiores sindicatos patronais são capazes de obter maior proteção comercial, em particular por meio de licenciamento não-automático; as estimativas sugerem que esse efeito é mais alto quando a penetração de importações aumenta mais intensamente, o que é interpretado como um aumento na necessidade de medidas de proteção.

Palavras-chave

Comércio Internacional; China; Mercado de Trabalho; Desigualdade; Equilíbrio Geral; Política Comercial; Economia Política; Interesses Especiais; Licenciamento Não-Automático; .

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Introduction

Following the death of Chairman Mao Zedong in 1976, the Popular Republic of China initiated a long and turbulent process of economic reform[1]. Led by Deng Xiaoping, the renewed leadership of the Chinese Communist Party gradually steered the country away from the maoist policies of the cultural revolution, starting from very basic steps such as reforming the agricultural sector and instituting private property. A central pillar of the reform plan rested on the opening of the economy to foreign interests: Deng's "open door policy" focused heavily on foreign investment as a means of industrial modernisation, and the first Special Economic Zones were installed as early as 1980, strategically located in the southeast coastal provinces of Guangdong and Fujian. By the end of the decade, economic and political unrest, fueled by rising inflation and symbolised by the Tiananmen Square protests, led to a brief period of counter-reform.

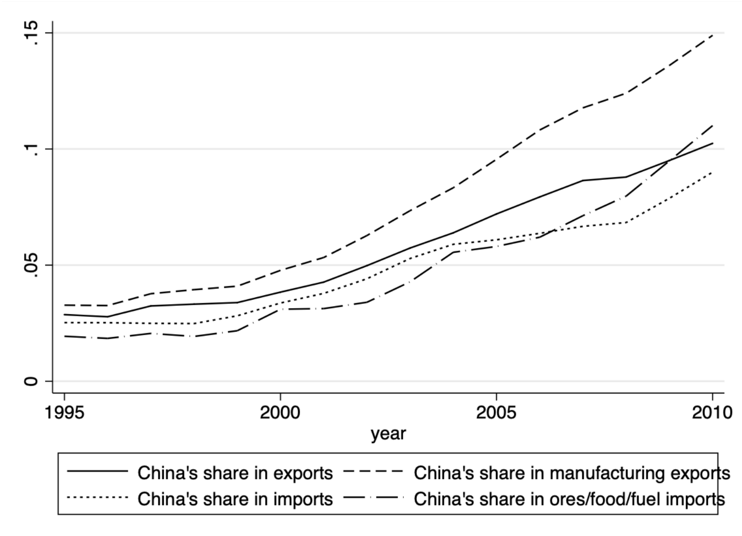
This brief intermission, however, wasn't able to stem the tide, and reform deepened in the early 1990s, especially after Deng's 1992 "southern tour" that helped securing support for his reformist agenda. One of the targets of this new wave of reforms was the country's trade system, and a series of measures were taken towards normalisation of its trade relations with other countries – a movement that culminated with the Chinese accession to the World Trade Organization in 2001, after a decade and a half of intense negotiations.

There is still much discussion surrounding China's joining of the WTO and whether the multilateral rules changed Chinese policy or rather the reverse; these polemics aside, it is clear that the accession was a milestone in a process that completely changed the role of China in the global economy. The turn of the XXIst century marked the dawn of China's unprecedented rise as a major trading power and one of the world's leading industrial powerhouses. Figure 1 illustrates this rise, plotting the fast-paced increase of Chinese participation in global trade flows. It also highlights one key aspect of this Chinese role as the "world's factory": the country's growing relevance as an exporter of manufactures and an importer of commodities. The rise of China in these two markets – and the resulting increased supply of industrial goods and demand for raw materials – came to be referred to by the literature as the "China

[1]For a detailed account of the Chinese reform process see, for example, Naughton (2007)

shock”[2]. The main purpose of this thesis is to shed light on distributional effects of this two-sided trade shock, as well as one of its political consequences.

Figure 1: Evolution of China’s Share in Merchandise Trade Flows



Source: World Development Indicators (World Bank)

The fact that trade shocks generate distributional effects, creating winners and losers, is acknowledged even by the simplest models of trade. Trade allows countries to reallocate resources to more efficient activities, the output of which are exchanged for other goods produced by other nations. It does not matter whether the higher efficiency stems from comparative advantage or from scale economies, for example; in order to realize gains from trade, it is inevitable that some reshuffling of resources will happen. Labor, capital and land used that were allocated to the less efficient production will have to seek employment elsewhere – the details depend on the particular model, but there will be winners and losers from the engagement in international trade.

The details, of course, may be crucial to determine the dimensions along which the cleavage between those who gain and those who lose will be set. For example, in the canonical two-by-two Hecksher-Ohlin framework, the split happens between factors of production – the Stolper-Samuelson theorem states that the factor used intensively in the production of the exported good will gain –, while in a Ricardo-Viner specific-factors model the split will be set along sectoral lines. In more recent models that emphasize firm heterogeneity there may be winners and losers even among capital owners in a same sector, depending on whether or not their firm is able to engage in trade.

[2]See, for example, Autor et al. (2016), and the references discussed in the following chapters.

Textbook expositions of trade usually emphasize that these effects could be offset by redistributing income from the winners to the losers, so that everyone would benefit from the increased aggregate welfare that trade allows. However, the reality is that a myriad of complications can preclude this seamless transition to the open, more efficient equilibrium. First, there may be search-related frictions in the labor market that hinder adjustment. Second, there may exist impediments or costs to mobility, preventing that labor or capital employed in declining activities move to the expanding ones – for example, workers may be forced to pay for retraining or move to other regions, which will be costly. These factors would lead to unemployment or idleness of resources, at least temporarily. Third, the existence of losers from trade can incentivize agents to organize themselves politically in order to block the institutional changes that could harm them – that is, so that the new equilibrium does not happen, which means that the (anticipated) distributional effects of trade can even prevent trade from taking place. This thesis analyzes all these mechanisms.

In Chapter 1, the main focus is the effect of the China shock on wage inequality in Brazil. The first part of the paper provides reduced-form evidence on this relationship, by comparing the effect among different micro-regions. I adopt a widely adopted strategy that translates sector-level shocks – in this case, the boom in exports to and imports from China that affected differently each sector – into region-level shocks, by constructing a measure of the exposition of each region to the shock that is based on the share of each sector in local employment. Endogeneity of trade outcomes to other local shocks is accounted for as is Costa et al. (2016), by instrumenting the evolution of bilateral trade between Brazil and China with a counterfactual trajectory based on a measure of Chinese push on global trade. The reduced-form evidence suggests that the foreign demand shock has led to a decline in the dispersion of wages in the tradable sectors, and this reduction seems to have worked mainly through the compression of average wages between firms, rather than by equalizing the wages of different workers in a same firm. The evidence also suggests that this wasn't the result of composition effects: on the contrary, the compression in between-firm inequality seems to stem from changes in firm behavior. Moreover, this change in behavior seems related to a decrease in the exporter wage premium – that is, although exporter firms on average pay higher wages across the whole period, this higher wage conditional on firm exporting status seems to have been negatively affected by the China demand shock.

Motivated by this reduced-form evidence, in the second part of Chapter

1 I employ a structural framework developed by Helpman et al. (2017), which incorporates the first of the three mechanisms mentioned above – matching frictions that preclude immediate adjustment and gives rise to a unobserved match-specific component of worker productivity, resulting in differences in wages conditional on exporting status, and leads to wage inequality between workers that are ex ante identical. An estimable reduced-form version of the model allows for counterfactual exercises exploring sectoral-level differences in the foreign demand shock, which affected distinctly across sectors the evolution of the ratio of foreign to domestic demand. The results of the counterfactual exercise suggest that this variable alone – that is, the China demand shock – can explain part of the observed aggregate reduction in the exporter wage premium and in wage dispersion.

In Chapter 2 I study the effects of the China shock on the dynamics of Brazilian labor market in an environment characterized by mobility costs that preclude immediate adjustment of the labor force in the face of price and wage changes – the second of the above discussed mechanisms. To do that, I use a version of the multi-country, multi-sector general equilibrium framework developed by Caliendo et al. (2019), which also incorporates features such as intermediate consumption, input-output linkages between sectors, productivity differentials at the country and firm levels and nontradable sectors.

In a nutshell, the model combines a dynamic discrete choice problem of labor supply based in Artuç et al. (2010) – in which families choose the sector in which they will seek employment, taking into account wages, mobility costs, and an idiosyncratic preference component – and, in each period, a static multi-sector Eaton-Kortum model with input-output linkages developed by Caliendo and Parro (2015) through which equilibrium wages and prices are defined. The model is solved using the technique also developed by Caliendo et al. (2019), in which the model is rewritten in terms of time differences and ratios of time differences, so that many of the model fundamentals cancel out, and the model can be simulated – and counterfactual exercises performed – without the need to estimate a huge set of parameters.

I also extend the model to allow for heterogeneity in worker skill, by assuming that firms combine skilled and unskilled labor into a composite labor factor. This allows for analyzing the relative demand for both types of labor and distributional effects of the China shock without taking strong assumptions regarding, for example, the degree of substitutability between each type of labor and other inputs, as in Parro (2013).

I then use the calibrated model to perform counterfactual exercises simulating the push on Brazilian exports and imports led by the Chinese sectoral productivity growth. Results from the homogeneous labor version suggest that the both sides of the China shock have contributed to the decline of manufacturing employment in Brazil in the first decade of this century, and that services sectors have absorbed most of the displaced workforce. Moreover, the import shock has also increased employment in mining and decreased in agriculture, and a reduction in unemployment and informality, while the export shock has driven an increase in both commodities sectors. However, overall the effects are modest, especially in the export shock; an alternative counterfactual scenario simulating the reprimarization of Brazilian export basket through shocks in local productivity suggest that the China shock is not enough to explain a significant part of the reshuffling of resources into commodities sectors.

Results of the counterfactuals with the heterogeneous-labor model suggest that distributional effects of the China shock are small, but consistent with reduced-form evidence obtained in Chapter 1, with the import shock reducing the share of unskilled workers in the nontradables sectors and increasing in the tradables sectors, and the export shock leading to an even smaller effect on the relative demand for labor types.

Finally, Chapter 3 tackles the third of the mechanisms discussed above: the political economy of trade policy and its relationship with trade shocks. Specifically, I try to provide an answer to the following question: when pressed by a surge in foreign competition – such as the China shock –, are industries with more political organization capable of obtaining more protection from foreign competitors than those who are less organized?

Evidently, such an endeavour is immediately complicated by the fact that since lobbying is illegal in Brazil, data on lobbying activities and political organization are nonexistent. I circumvent this limitation by focusing on lobbying by trade associations or employer unions, through which firms in a same sector organize themselves to advance common special interests – that is, through which firms "lobby together", as in Bombardini and Trebbi (2012). This form of joint lobbying is particularly relevant for policies that are implemented at the product or industry level – which is usually the case of trade policy.

With this in mind, I assemble a novel dataset on Brazilian trade associations in order to construct measures of political organization at industry level, based on the size of the associations that represent each sector. I then use variation in these measures to verify whether sectors with more organization capacity have greater levels of trade protection. I also examine whether the increase in import penetration augments this effect of political organization on protection; the rationale being that, when competition stiffens – as represented by an increase in import penetration –, industries will be more pressed to dedicate their lobbying apparatus to increase the barriers that insulate the domestic market. To account for the possible endogeneity in the import penetration measure – whose behavior could be capturing the effect of local phenomena such as industry-level shocks – I focus on the China shock as a plausibly exogenous source of foreign competition, using as instrument a "counterfactual" trajectory of bilateral Brazilian imports from China obtained by multiplying baseline trade levels with a measure of the excess growth rate of China's exports in a given sector in comparison with the world average, as in the first part of Chapter 1.

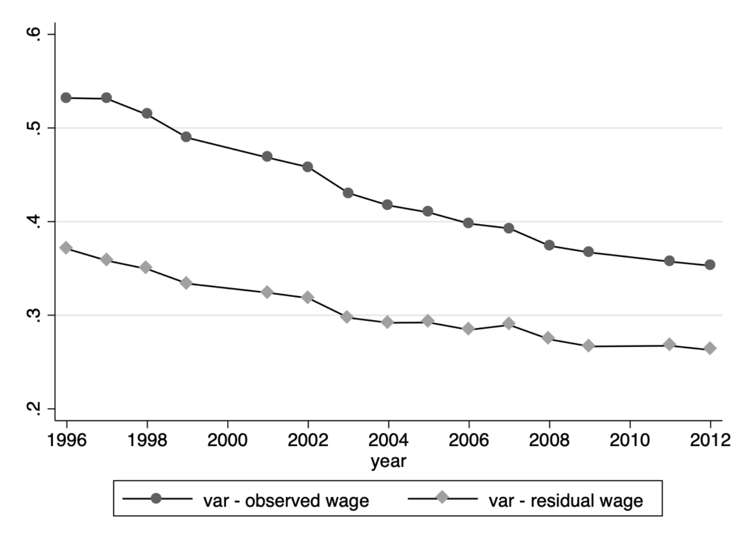
The evidence suggest that, particularly in one type of non-tariff measure (non-automatic licensing), sectors with larger trade associations are indeed more successful in obtaining protection from imports, and this effect is larger for industries that are subject to increased import penetration, suggesting that industries may be taking advantage of their lobbying capabilities to procure protection from foreign competition when this protection is most needed. This effect is robust to accounting for the role of factors that may be related to the size of an industry's trade union, such as the size of its worker union, or that could affect the level of protection, such as the share of intermediate products in a given industry. I also present suggestive evidence that the variation in trade association size may be inversely related to the evolution of an industry's productivity, which could indicate that industries turn to rent-seeking activities when their competitiveness is lacking, in consonance with a framework in which lobbying for protection is a substitute for cost-reducing activities or costly adjustment to negative shocks.

1
Trade and Wage Inequality: Evidence from the China Shock on Brazil

1.1
Introduction

There is ample evidence of a sustained process of reduction in wage inequality in Brazil, starting in the mid-late 1990s and peaking in the 2010s. This trend – which is also present in other latin-american countries, and in stark contrast to many developed nations such as the US – is illustrated in Figure 1.1, which plots the evolution of wage variance in Brazil from 1996 to 2012. As the figure shows, variance in log wages underwent a significant (and almost monotonic) reduction in the period. This is true even if one filters out the effect of changes socio-demographic characteristics of the workforce by focusing on the residuals of a Mincerian wage regression.

Figure 1.1: Evolution of Log Wage Variance

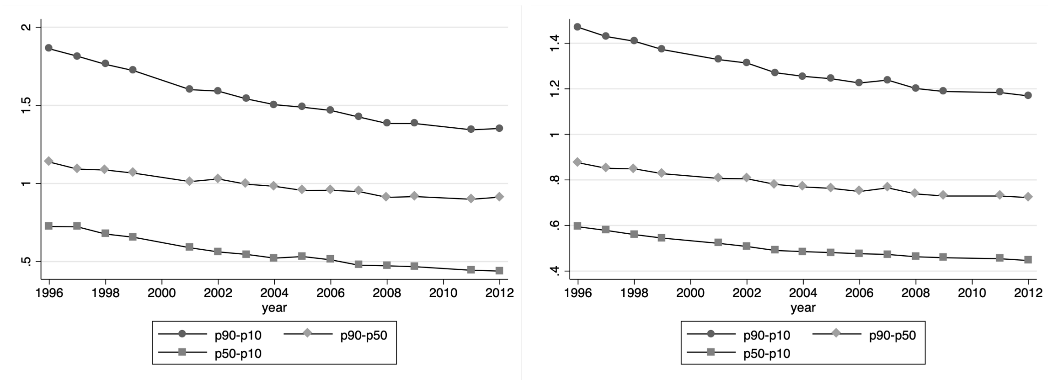


Source: PNAD/IBGE

One significant characteristic of this reduction in wage inequality is the fact that it was even more pronounced in the lower portion of the wage distribution. Figure 1.2 plots the evolution in differentials between selected percentiles of the log wage distribution, and shows that even though one may see a decline in all of the curves, the reduction in the gap between the median and first decile is more intense than the compression in the disparity between the 90th percentile and the median.

Figure 1.2: Wage Differentials Between Percentiles

(a) Observed Log Wages (b) Residual Wages



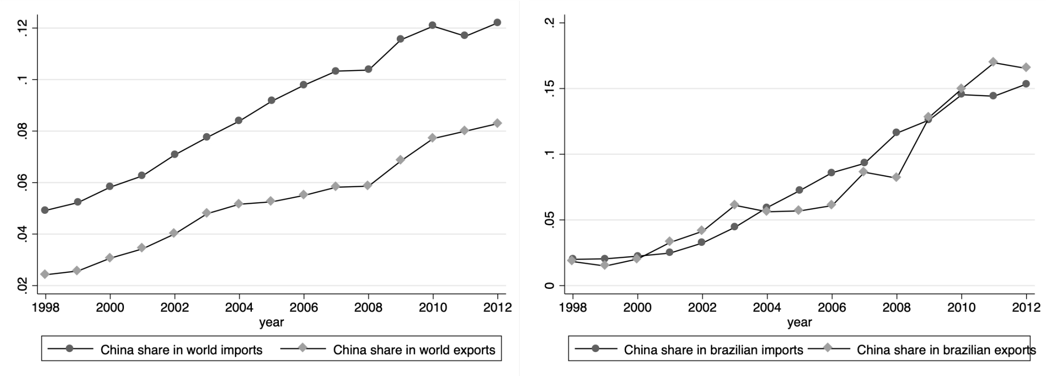
Source: PNAD/IBGE

A similar conclusion was reached by Alvarez et al. (2018): they show that although wage differentials decreased along the whole wage distribution, the magnitude of the reduction is larger in the lower portions – while the p90-p50 ratio fell by 26 log points, the p50-p10 and p50-p5 gaps fell by 38 and 53 log points, respectively, between 1996 and 2012.

A number of potential explanations for this trend have been suggested by the literature, ranging from a reduction in returns to worker characteristics such as skill or experience – which can be the visible manifestations of underlying economic processes such as the trade liberalization – to institutional factors such as the increase in real minimum wages. This paper aims to contribute to this discussion by shedding light on a possible candidate for this process: the "China shock", the rapid increase in both imports and exports driven by the emergence of China as a major trade player.

As figure 1.3 illustrates, the country has gained increasing importance in global trade, and Brazil is no exception – in fact, China's share in Brazilian market has increased more than it's participation in global trade, as shown in the right panel.

Figure 1.3: Chinese Participation in International Trade



Source: BACI/CEPII

The goal of this paper, therefore, is to examine what was the impact of the China export and import shock on Brazilian labor market outcomes, and in particular on the wage distribution.

In order identify the relationship between the rise of China and Brazilian labor market outcomes, we employ two empirical strategies. In the first part of this paper, we adopt a shift-share design similar to the one used by Autor et al. (2013) and many others, that focuses on heterogeneous effects of the shock among local labor markets, using a measure of how each region was affected by the surge in Chinese exports and imports. By doing so, it is possible to isolate the effect from that of potential confounders determined at the national level, such as the national minimum wage. To account for the probable endogeneity of trade outcomes to other local shocks, we follow Costa et al. (2016) and instrument the evolution of bilateral trade between Brazil and China with a counterfactual trajectory based on a measure of Chinese push on global trade.

The results show that the foreign demand shock on Brazilian exports has led to a decline in the dispersion of wages in the tradable sectors: regions with higher exposure to the export shock experienced larger reductions in wage variance and in the 90-10 and 50-10 percentile gaps. We also show that this reduction seems to have worked mainly through the compression of average wages between firms, rather than by equalizing the wages of different workers within firms. The evidence also shows that the China export shock has directly affected firm average wages in tradables, reducing their dispersion, but didn't affect significantly the employment shares of firms in different sections of the average wage distribution – suggesting that the compression in the between-firm component of wage variance was driven by changes in firm behavior, rather than composition effects. Moreover, this change in behavior seems to be related to a decrease in the exporter wage premium – that is, although exporter firms on average pay higher wages across the whole period, this higher wage conditional on firm exporting status seems to have been negatively affected by the China demand shock.

This reduced-form evidence, however, is not without its limitations: the empirical strategy implies that the results are only informative about the relative effects across regions, providing no insight on the overall impact of the China shock on the Brazilian economy as a whole. Therefore, to be able to speak more generally about the net effects of the rise of China on wage inequality – and motivated by the reduced-form evidence –, in the second part of the paper we employ a structural framework developed by Helpman et al. (2017), which features firm heterogeneity and fixed costs of exporting – leading to differences in firm productivity conditional on exporting status. The model also incorporates matching frictions and unobserved match-specific component of worker productivity, resulting in differences not only in productivity but also in wages conditional on exporting status, and leading to wage inequality between workers that are *ex ante* identical. We use the estimated model to perform counterfactual exercises exploring sectoral-level differences in the foreign demand shock, which affected distinctly across sectors the evolution of the ratio of foreign to domestic demand, to show that this variable alone – that is, the China demand shock – can explain part of the observed aggregate reduction in the exporter wage premium and in wage dispersion.

This paper contributes to a vast empirical literature on labor market effects of trade shocks, particularly on wage inequality; Pavcnik (2017) presents a detailed review. A strand of this literature focused on episodes of trade liberalization, such as the one experienced by Brazil in the late 1980s through the early 1990s; however, the evidence gathered is mixed. Pavcnik (2004), for example, show that trade liberalization did not affect wage differentials between sectors, while Gonzaga et al. (2006) found evidence consistent with trade liberalization reducing relative earnings between skilled and unskilled workers. Ferreira and Wai-Poi (2007), however, argue that while liberalization seems to have contributed to the reduction in wage inequality, it seems to have worked via employment flows across sectors, and not through sector-specific skill premia.

A more recent set of papers paint a less favorable picture of the effect of the trade liberalization episode on labor markets, by focusing on the differential impacts of opening to imports across local labor markets. While Dix-Carneiro and Kovak (2015) found that liberalization led to a small decline on the skill premium, additional work by the same authors (Dix-Carneiro and Kovak (2017)) concluded that it also caused a large and persistent decline in formal employment and earnings, which is compounded by sluggish capital adjustment and imperfect mobility of labor across regions even in the long run, which precludes the expected damping of the effects that would occur if workers from harder hit labor markets could move seeking better prospects. Dix-Carneiro et al. (2018), moreover, suggest that these negative labor market effects may have relevant social implications, by showing that the regions more affected by trade liberalization experienced an increase in criminality.

A large number of papers have also followed this strategy that compares the effect of a trade shock across regional labor markets by constructing a Bartik (1991)-like measures of how a sector-specific shock have affected each region; for example, Topalova (2010) followed this route to examine the effects of trade liberalization on poverty in India, while Hakobyan and McLaren (2016) focused in the effects of NAFTA, and Ulyssea and Ponczek (2018) used this approach to analyze how the enforcement of labor regulation mediated the impact of trade opening on Brazilian informal employment.

Autor et al. (2013) was probably the first paper to adopt this strategy to examine labor market effects of the emergence of China as a major economic player, showing that United States' commuting zones more exposed to Chinese import competition experienced declines in manufacturing employment and wages. Costa et al. (2016) follows the same idea, while noting that for commodity-exporting countries the rise of China wasn't only a negative import competition shock, but also a positive export demand shock that stemmed from the Asian giant's growing appetite especially for agricultural and mineral goods. In consonance with this dual-sided nature of the China shock, they show that while Brazilian regions more affected by Chinese import competition suffered slower growth manufacturing wages – in a similar effect to the one found by Autor et al. (2013) for the United States –, those that benefited from higher Chinese demand for commodities experienced higher wage growth.

My contribution to this literature is to adopt a similar strategy to analyze the effect of the dual China shock on the Brazilian wage distribution. In this regard, this chapter differs from previous attempts (such as Costa et al. (2016)) for not restricting the focus to wage differentials between types of workers (such as skilled and non-skilled), but rather analyzing the effects on wage dispersion and gaps between percentiles of the wage distribution, and also focusing on residual wages that control for workers' observable characteristics.

This paper is also related to an extensive literature that developed trade models with labor market frictions to analyze labor market effects of trade shocks in frameworks that depart from the traditional neoclassical predictions *à la* Stolper and Samuelson (1941). Davidson et al. (1999) were arguably the first to embed a labor market with search and matching frictions into a simple trade model and show that the effect of trade on factor returns depends on the assumptions made about the bargaining over revenue, and while the Stolper-Samuelson can be extended to searching factors, the effect on employed factors also include forces that resemble a specific factors model; the paper also describes the effect on *unemployed* factors – which of course cannot be compared to traditional, full-employment trade models. Helpman and Itskhoki (2010) also introduce search and matching frictions in a trade model, but one with monopolistic competition in differentiated products and firm heterogeneity as in Melitz (2003). Helpman et al. (2010) further extends this framework to include also heterogeneity in workers' ability, which allows the analysis of the effects of trade on wage inequality. Interestingly, heterogeneity in ability arises ex post even though all workers are ex ante identical, which gives rise to wage inequality even among workers that have the same observable characteristics – thus disentangling wage inequality from skill, experience or sector premia, for example. Helpman et al. (2017) use an estimable version of this framework and Brazilian data to analyze the effect of trade liberalization on wage inequality, showing that the relationship between openness and (residual) inequality resembles and inverted U – that is, inequality increases after the country departs from autarky, but as trade participation deepens inequality eventually starts to decline. In section 1.3, we argue that the China shock may have taken the Brazilian economy to the region where trade is inequality-reducing.

This paper also contributes to a literature dedicated to analyzing the dynamics of inequality in Brazil and explaining the determinants of its decline, especially during the first decade of the XXth century. The question is still open, and the literature – thoroughly reviewed by Firpo and Portella (2019) – identifies a host of suspects, apart from the trade shocks already discussed. A number of papers – such as Ferreira et al. (2008, 2014, 2017), Alvarez et al. (2018), and Fernández and Messina (2018) – have pointed to changes in relative supply of education and experience, leading to changes in composition and returns to these observables, both of which may have contributed to the reduction in wage inequality. Alvarez et al. (2018) also highlights the role of firms, namely the reduction in the pass-through of firm productivity to wages, which could have helped compress the wage distribution. Other institutional factors may have also contributed to the decline in wage inequality, such as the sustained rise in minimum wage – according to Corseuil et al. (2015), Saltiel and Urzúa (2017) and Engbom and Moser (2018), for example – and the increase in formality – as pointed out by Ferreira et al. (2017). My contribution is to examine the role of foreign trade and the China shock in this process, and in particular to highlight the role of changes in firm behavior – such as the wage premium of exporter firms – in the recent decline of wage inequality in Brazil.

The paper is organized as follows. Section 2 explores the reduced-form evidence, presenting the data sources, discussing the empirical strategy and reporting the results. Section 3 presents the structural model and its reduced-form econometric version, as well as the counterfactual exercise. Section 4 presents the concluding remarks.

1.2 Reduced-Form Evidence

The purpose of this section is to provide evidence on the role of the China shock in the reduction of wage inequality in Brazil during the first decade of the XXth century. To do so, we employ a strategy that is widely used in the literature about labor market effects of trade shocks, which focuses on comparing the effects of the shock between different regions or local labor markets. The idea behind this strategy is to translate a sector-level shock – in this case, the boom in exports to and imports from China that affected differently each sector – into a region-level shock, by constructing a measure of the exposition of each region to the shock that is based on the share of each sector in local employment.

This section presents the data employed in this analysis, details the empirical strategy and discusses the results and their implications. We focus on four sets of reduced-form results. First, we present general effects of the China shock on employment and informality. Second, we present our main results, which show that the export facet of the China shock has contributed to the decline in wage inequality across micro-regions in Brazil, an that this reduction was mainly due to the compression of average wages between firms. We then examine whether this latter outcome was due to actual changes in firm behavior or to composition effects. Finally, we examine the role of the wage premium paid by exporter firms as a mechanism contributing this development.

1.2.1 Data

The analysis is based on four main datasets. The first is *Relação Anual de Informações Sociais* (RAIS), which is a yearly matched employer-employee dataset provided by the Brazilian Ministry of Labor that encompasses the whole of the Brazilian formal labor market. Its unit of record is a formal employment contract, and has information on characteristics of the worker and of the firm involved. However, as mentioned, it comprises only the formal sector of the labor market, providing no information at all about informal or self-employed individuals. We restrict the sample to individuals between 18 and 64 years old working at least 30 hours per week as employees or self-employed in the private sector. Data was deflated using the Brazilian Consumer Price Index (INPC)

The second main data source is the Brazilian Demographic Census, that provides individual-level data on socio-demographic and economic characteristics for a sample of individuals, from age and education to employment status and wages. One advantage over RAIS is that it includes information on both formal and informal workers. Apart from this, the sample is defined analogously as that from RAIS data. The Census is conducted by the Brazilian Institute of Geography and Statistics every ten years[1]. We focus on the 2000 and 2010 Census, but data from the 1991 edition is also used as controls.

Third, we use trade data from the BACI database, developed by Centre d'Etudes Prospectives et d'Informations Internationales (CEPII), which reconciles the declarations given by exporters and importers to reduce inconsistencies in the original UN Statistics Division's COMTRADE data. Finally, we also explore data on exporter status of Brazilian firms, which is made available by the Foreign Trade Secretariat of the Brazilian Ministry of the Economy.

The definition of local labor market adopted as unit of analysis is a micro-region – that is, a set of municipalities which are economically integrated –, defined by the IBGE, and extensively used in the literature for Brazil (e.g. Costa et al. (2016); Dix-Carneiro and Kovak (2015, 2017); Dix-Carneiro et al. (2018)). The mapping from municipalities to micro-regions used in this paper is consistent between 1990 and 2010, and has a total of 413 micro-regions.

[1]The exception is 1991, which would be conducted in 1990 but was delayed.

Table 1.1: Micro-Region Level Summary Statistics

	Observations	Mean	S.D.	Min.	Max.
Panel A: 2010-2000 Difference in Observed Log Wage Inequality Measures					
Variance	413	-0.16	0.16	-0.92	1.04
p90-p10	413	-0.36	0.35	-1.95	2.21
p90-p50	413	-0.22	0.29	-1.46	0.87
p50-p10	413	-0.14	0.20	-1.27	1.90
Variance (Nontradables)	413	-0.20	0.18	-1.08	1.04
p90-p10 (Nontradables)	413	-0.44	0.38	-2.04	2.21
p90-p50 (Nontradables)	413	-0.26	0.32	-1.43	0.90
p50-p10 (Nontradables)	413	-0.18	0.23	-2.37	1.90
Variance (Tradables)	408	-0.09	0.20	-1.57	1.38
p90-p10 (Tradables)	409	-0.21	0.41	-2.30	2.05
p90-p50 (Tradables)	409	-0.11	0.35	-2.62	1.87
p50-p10 (Tradables)	409	-0.10	0.19	-0.87	1.65
Panel B: 2010-2000 Difference in Residual Wage Inequality Measures					
Variance	413	-0.12	0.12	-0.74	0.92
p90-p10	413	-0.30	0.28	-1.79	2.22
p90-p50	413	-0.15	0.21	-1.22	0.60
p50-p10	413	-0.15	0.13	-1.04	1.66
Variance (Nontradables)	413	-0.15	0.13	-0.77	0.92
p90-p10 (Nontradables)	413	-0.36	0.31	-1.80	2.22
p90-p50 (Nontradables)	413	-0.20	0.24	-1.28	0.63
p50-p10 (Nontradables)	413	-0.16	0.15	-1.29	1.66
Variance (Tradables)	408	-0.06	0.12	-0.86	0.86
p90-p10 (Tradables)	409	-0.20	0.28	-1.77	1.47
p90-p50 (Tradables)	409	-0.07	0.22	-1.64	1.45
p50-p10 (Tradables)	409	-0.12	0.12	-0.71	1.13
Panel C: 2010-2000 Difference in Employment					
Occupied/Working-Age Population	413	0.01	0.03	-0.08	0.09
Occupied/WAP (Nontradables)	413	0.00	0.02	-0.05	0.07
Occupied/WAP (Tradables)	413	-0.02	0.02	-0.07	0.05
Panel D: Measures of Shocks					
Export Shock	413	0.56	0.96	0.01	4.97
Import Shock	413	0.47	0.48	0.09	2.75
Panel E: Micro-Region Level Controls (1991 levels)					
Share Female	413	0.50	0.02	0.38	0.54
Share High School	413	0.12	0.06	0.02	0.35
Share Informal Workers	413	0.44	0.20	0.07	0.94

Notes: Descriptive statistics for the variables used in this paper. Wage data from RAIS. Employment data and demographic controls from Census. For details on the construction of measures of shocks see Section 1.2.2.

1.2.2 Empirical Strategy

The main purpose of this section is to plausibly identify causal effects of trade shocks on the labor market, focusing on the role played by the so-called “China shock” – the trade effects of the rise of China as a major trading power in the dawn of the XXIst century – in the labor market transformations that have taken place in Brazil in the first decade of this century which led to a reduction in wage inequality. In this subsection we describe the empirical strategy adopted to undertake this task.

One of the major problems in identifying the effect of trade shocks is that, since these occur in general equilibrium, a large number of confounders may hinder the identification of the mechanisms of interest to the researcher. A route taken by a vast part of the literature (at least since Topalova (2010), and since Autor et al. (2013) for the China shock) to circumvent this problem is to focus on the differential effect of the shock on local labor markets, using measures of regional impact that are analogous to the shift-share instruments introduced by Bartik (1991), in which the shock on each industry is weighted by their share in regional employment to obtain a region-specific measure of the intensity of the shock.

Specifically, let the country-wide import shock to industry i be denoted as $\Delta I_i \equiv I_{i1} - I_{i0}$, where I_{it} is the value of Brazilian imports of Chinese products from that sector in period t. Then, the region-specific measure of the import shock on local labor market m is given by:

$$IS_m = \sum_i \frac{\lambda_{mi0}}{\lambda_{i0}\lambda_{m0}} \Delta I_i \tag{1-1}$$

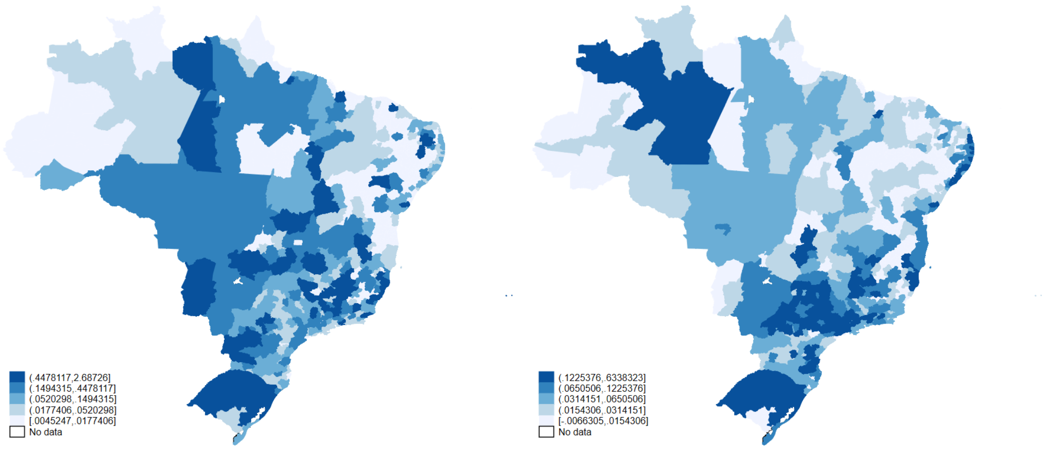
where λ_{mi0} is the size of region m's workforce employed in industry i in the baseline period, λ_{i0} is the country's workforce employed in that sector, and λ_{m0} is the total labor force available in m.

As Costa et al. (2016) show, the China shock represents not only an increase in the supply of imported products (as is the focus of the literature concerned with its negative effects on the US labor markets, such as Autor et al. (2013)), but also an increase in the demand for a number of products, especially mineral and agricultural commodities, that amount for a large share of Brazil's exports. We can therefore define the export shock that affects region m as:

$$XD_m = \sum_i \frac{\lambda_{mi0}}{\lambda_{i0}\lambda_{m0}} \Delta X_i \tag{1-2}$$

where ΔX_i represents the increase in the value of Brazilian exports to China, and is defined analogously to ΔM_i. Figure 1.4 displays the geographical distribution of the two shocks for our main time frame (that is, with 2000 as $t = 0$ and 2010 as $t = 1$).

Figure 1.4: Geographic Distribution of Shocks



Export Demand Shock | Import Supply Shock

These measures of the two faces of the China shock are used as the main regressors in the empirical analyses reported in the next sections, which take the following form:

$$\Delta Y_m = \alpha_s + \beta_1 IS_m + \beta_2 XD_m + \Gamma D_m + \epsilon_m \tag{1-3}$$

where Y_m are the outcomes of interest, α_s are state fixed-effects to control for state-specific trends, and D_m is a vector of microregion-level predetermined demographic characteristics (given that the shocks may be correlated to these characteristics) which include the shares of female workers, high-school graduates and informal workers in 1991. The main specifications also include the lagged[2] level of the outcome Y_m, to account for the possibility that the shocks could be correlated with predetermined trends in these variables. Standard errors are clustered at the meso-region level[3] to allow for spatial correlation across adjacent micro-regions. In light of the growing literature focused on methodological aspects of shift-share strategies, we have also estimated all regressions employing the procedure developed by Adão et al. (2019) to obtain standard errors that account for the possible correlation between distant micro-regions with similar employment patterns.

The identification hypothesis underlying the regression in equation (1-3) would be that the measures of the China shock should be exogenous to other

[2]For the outcomes obtained from the demographic census we used the previous edition, from 1991; for those obtained from RAIS, we used the closest substitute, the 1994 edition – given that some of the variables were unavailable or differently coded in previous years.

[3]The level of aggregation above micro-region.

economic conditions that could affect the outcomes Y_m. An obvious concern stems from the fact that the measures of the shock are based on the growth of Brazilian exports and imports, which may be capturing the effect of other phenomena – such as industry-level shocks –, so that IS_m and XD_m would be correlated with ϵ_m. The path usually taken by the literature to deal with this issue is to instrument the observed growth in bilateral trade with the growth in Chinese trade with other (allegedly similar) countries – for example, using the growth in trade between China and a set of developed countries to instrument for the evolution of trade between the US and China. We follow Costa et al. (2016) in taking a slightly different track, which deals also with the possibility of correlated world-level shocks which could also hinder identification. Instead of directly using information on Chinese trade with other countries, the instruments proposed by Costa et al. (2016) for the growth in Brazilian trade with China are based on a "counterfactual" measure of this growth, obtained by multiplying baseline trade levels with the excess growth rate of China's imports and exports in a given sector in comparison with the world average. This Chinese excess growth rate is obtained from the following set of auxiliary regressions:

$$\frac{I^*_{ci1} - I^*_{ci0}}{I^*_{ci0}} = \tau_i + \psi_{China,i} + \zeta_{ci}$$
$$\frac{X^*_{ci1} - X^*_{ci0}}{X^*_{ci0}} = \pi_i + \delta_{China,i} + \xi_{ci}$$

where I^*_{cit} and X^*_{cit} are, respectively, industry i's imports and exports of country c from (to) all countries except Brazil. These regressions are weighted by the baseline trade values.

The industry fixed effects, τ_i and π_i, captures the sector's average growth rate across all countries (except Brazil), thus accounting for world-level shocks. The China-sector dummies $\psi_{China,i}$ and $\delta_{China,i}$, therefore, capture the deviation in growth rates of Chinese trade in industry i from this countrywide average – that is, the excess contribution of China to the growth rate of imports or exports of that sector.

The "counterfactual" growth in Brazilian imports from and exports to China are then given by $\Delta\hat{I}_i = I_{i0}\delta_{China,i}$ and $\Delta\hat{X}_i = X_{i0}\psi_{China,i}$. The instrumental variables are therefore:

$$ivIS_m = \sum_i \frac{\lambda_{mi0}}{\lambda_{i0}\lambda_{m0}}\Delta\hat{I}_i \tag{1-4}$$

and

$$ivXD_m = \sum_i \frac{\lambda_{mi0}}{\lambda_{i0}\lambda_{m0}} \Delta \hat{X}_i \tag{1-5}$$

The main outcomes that are analyzed in this paper are the wage variance and three gaps between between percentiles of the wage distribution calculated from RAIS data – namely, between the 90th and 10th, 90th and 50th, and 50th and 10th percentiles – that summarize the effect on different portions of the wage distribution. These measures are obtained both from the observed (monthly and hourly) log wages and from the residual wages obtained from a standard Mincerian regression (which includes education, age, age squared, race, gender and state dummies); the latter procedure isolates the effect of changes in the socio-demographic composition of the workforce, which can also affect the wage distribution.

Apart from these four inequality measures, other aggregate labor market outcomes – namely, measures of occupation/employment and informality – are also examined, using Census microdata. To calculate these outcomes by micro-region, while netting out the effect of socio-demographic characteristics of the sample, we proceed as Dix-Carneiro and Kovak (2017) and run, for each year, Mincer-like regressions including a set of dummies for the micro-regions, M_{mt}:

$$Y_{jmt} = \sum_m \mu_{mt} M_{mt} + \Theta_t X_{jt} + \epsilon_{it} \tag{1-6}$$

where j index individuals, and X_{jt} is a vector of individual-level socio-demographic characteristics (gender, race, education, age and age squared). Therefore, the coefficients on the regional dummies, μ_{mt}, provides a measure of each outcome at the micro-region level. These measures are then time-differenced to be used as regressands in (1-3).

1.2.3 Effects of the China shock on Employment and Informality

In this subsection, we present some general results on the effect of the China shock on employment and informality. The main data source thus is the population census, since RAIS is restricted to the formal sector only. As discussed in subsection 1.2.2, the outcome variables are obtained as the coefficients of micro-region dummies in Mincer-type equations, and thus provide a measure of each quantity of interest at the micro-region level.

First, we focus on employment, broadly measured as the number of occupied workers as a share of the working-age population[4]. As table 1.2 shows, the microregions more exposed to the export shock seem to have increased employment, particularly in the tradables sector – as column 4 shows, there seems to have been a shift from nontradables to tradables among the workforce. The implied relative magnitudes are such that, if one compares a microregion in the 90th percentile of shock exposure to one in the 10th percentile, the increase in employment is equivalent to 12% of a standard deviation of the micro-regions' changes in employment between 2000 and 2010; the magnitudes for occupied in tradables both as a share of working-age population and of occupied workers are very similar (12% and 10%, respectively). The import shock has no meaningful effects.

We then turn our attention to informality. We define formal employees as those who have a formal employment contract registered in their workers' identification booklet ("carteira de trabalho"). As displayed in table 1.3, the increase in employment caused by the export shock worked mainly though the formal sector: formal employees have increased both as a share of occupied workers and as a share of employees, while both informal and self-employed workers have decreased as a share of the workforce (magnitudes are also very similar to those of employment effects). Interestingly, the import shock also seems to have led to a similar effect, although the estimates are less precise.

In Appendix A.1, we investigate the how the effect on informality is distributed across sectors (tradable and nontradable). The results suggest that the increase in formal contracts caused by the export shock seems to have been driven by the tradables sector, while the corresponding decrease in informality and self-employment happened in the nontradables sector – that is, the increase in exports induced by the rise of China has led to a shift in the labor force from informal jobs in the nontradables sector to formal jobs in the tradables sector.

[4]Similar results are obtained if we measure employment as the number of employees as a share of the working age population – that is, eliminating self-employed workers.

Table 1.2: Effects on Employment

2010-00 diff. in:	(1) Occupied / WAP	(2) Occupied (Tradables) / WAP	(3) Occupied (Nontradables) / WAP	(4) Occupied (Tradables) / Occupied
Export Shock	0.003	0.002	0.001	0.003
	(0.001)***	(0.001)**	(0.001)	(0.002)**
Import Shock	0.001	0.000	-0.001	-0.001
	(0.003)	(0.002)	(0.003)	(0.005)
State FE	yes	yes	yes	yes
Dem. Controls	yes	yes	yes	yes
Observations	413	413	413	413
R-squared	0.551	0.310	0.441	0.291

Notes: this table reports the effects of Chinese export and import shock on the 2010-2000 difference in measures of employment at the micro-region level. All columns report the results of 2SLS regressions where the regressands are measures of employment (excluding public-sector employment), and the variables of interest are the micro-region-level measures of exposure to the China export and import shock, instrumented using measures of the excess contribution of China to the growth rate of world imports and exports (excluding Brazil) in a given sector, as described in section 1.2.2. “Occupied” include formal and informal employees and self-employed individuals (excluding employers). “WAP” refers to all individuals in the working-age population (18-64). Measures of employment are obtained as the coefficients on micro-region dummies in Mincer-like regressions of the variable of interest on a vector of individual-level socio-demographic characteristics (gender, race, education, age and age squared). All specifications include State dummies and control for demographic characteristics of the micro-regions (shares of female workers and of high-school graduates in 1991). Standard errors (in parentheses) are clustered at the meso-region level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Taken together, the results presented in this section suggest that the export side of the China shock – that is, the increase in exports induced by the rise of China – has led to an expansion of the employment in tradables, attracting workers from the nontradables sector, from informal labor, and from out of the labor force. The effects of import side of the China shock, however, are much less clear.

Table 1.3: Effects on Informality

2010-00 diff. in:	(1) Formal Employees / Occupied	(2) Informal Employees / Occupied	(3) Self-Employed / Occupied	(4) Informal Employees / Employees
Export Shock	0.005	-0.003	-0.003	-0.004
	(0.002)***	(0.001)***	(0.001)**	(0.002)**
Import Shock	0.010	-0.008	0.001	-0.011
	(0.005)*	(0.004)**	(0.003)	(0.006)*
State FE	yes	yes	yes	yes
Dem. Controls	yes	yes	yes	yes
Observations	413	413	413	413
R-squared	0.309	0.553	0.391	0.378

Notes: this table reports the effects of Chinese export and import shock on the 2010-2000 difference in measures of formality and informality at the micro-region level. All columns report the results of 2SLS regressions where the regressands are measures of informality, and the variables of interest are the micro-region-level measures of exposure to the China export and import shock, instrumented using measures of the excess contribution of China to the growth rate of world imports and exports (excluding Brazil) in a given sector, as described in section 1.2.2. "Occupied" include formal and informal employees and self-employed individuals (excluding employers). "Formal" refers to employees that have an active formal employment contract. Measures of employment and formality are obtained as the coefficients on micro-region dummies in Mincer-like regressions of the variable of interest on a vector of individual-level socio-demographic characteristics (gender, race, education, age and age squared). All specifications include State dummies and control for demographic characteristics of the micro-regions (shares of female workers and of high-school graduates in 1991). Standard errors (in parentheses) are clustered at the meso-region level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

1.2.4 Effects of the China Shock on Wage Inequality

This section presents the main results of regressions of the form (1-3) focusing on the measures of wage inequality – namely, wage variance and the gaps between the 90th and the 10th, the 90th and the 50th, and the 50th and the 10th percentiles of the distribution of log wages. Tables 1.4 and 1.5 display the results for observed (panel A) and residual (panel B) monthly wages (hourly wages yield similar results, which are presented in the appendix[5]). All regressions include both shocks and are estimated by two-

[5] It should be noted that roughly 85% of each year's observations have exactly 44 weekly hours worked (which is the legal maximum in Brazil), and almost 95% work at least 40 hours per week. Moreover, information on hours in RAIS refers to contractual hours, rather than hours effectively worked, which can be misleading. For these reasons, we opt to focus on monthly wages, and leave hourly wages to the Appendix.

stage least squares (using the instruments discussed in the last section), are weighted by micro-region population, and include State fixed effects and micro-region-level demographic controls fixed at the 1991 Census level (additional specifications are presented Appendix A.2.2). Standard errors are clustered at the meso-region level, to allow for arbitrary correlation among close micro-regions. As discussed in section 1.2.2, we have also used the procedure in Adão et al. (2019) to obtain standard errors that account for the possible correlation between distant micro-regions with similar employment patterns. Results are presented in Appendix A.2.1; it should be stressed that even though some standard errors are indeed larger than those of the main specifications with clustering, the vast majority of the estimates presented in this and the following subsections maintain the same levels of statistical significance.

Table 1.4: Effects of the China Shock on Inequality

2010-00 diff. in:	(1) Variance	(2) p90-p10 gap	(3) p90-p50 gap	(4) p50-p10 gap
Panel A: observed (log) wages				
Export Shock	-0.001	0.007	0.004	0.003
	(0.005)	(0.011)	(0.009)	(0.006)
Import Shock	-0.005	0.007	-0.018	0.025
	(0.008)	(0.024)	(0.026)	(0.013)*
R-squared	0.364	0.360	0.413	0.347
Panel B: residual wages				
Export Shock	-0.002	-0.003	0.001	-0.003
	(0.003)	(0.007)	(0.006)	(0.003)
Import Shock	-0.006	-0.009	-0.019	0.011
	(0.007)	(0.020)	(0.020)	(0.007)
R-squared	0.501	0.452	0.483	0.264
Observations	413	413	413	413

Notes: this table reports the effects of Chinese export and import shock on the 2010-2000 difference in measures of wage inequality at the micro-region level. All columns report the results of 2SLS regressions where the regressands are measures of wage inequality, and the variables of interest are the micro-region-level measures of exposure to the China export and import shock, instrumented using measures of the excess contribution of China to the growth rate of world imports and exports (excluding Brazil) in a given sector, as described in section 1.2.2. “p90-p10” refers to the log ratio of the percentiles 90 and 10 of the wage distribution, and similarly for “p90-p50” and “p50-p10”. Measures of inequality are calculated from observed wages (panel A) and from the residuals of Mincerian regressions including education, age, age squared, race, gender and state dummies (panel B). All specifications include State dummies and control for demographic characteristics of the micro-regions (shares of female workers and of high-school graduates in 1991) and for the 1991 level of the dependent variables. Standard errors (in parentheses) are clustered at the meso-region level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

As one can notice from the results on table 1.4, there are no visible effects of any of the two "China shocks" on wage inequality when the full sample is considered. The coefficients for the export demand shock (XD) are very small and statistically insignificant. For the import demand shock (IS), the coefficients are very imprecisely estimated – the positive one for the effect on the p50-p10 gap is significant at the 10% level for observed wages, but not for residual wages.

These results, however, are based on a sample that includes the entire formal workforce (aside, of course, for the sample restrictions mentioned above), therefore lumping together subsets of the labor market that probably respond very differently to a trade shock – one obvious dimension is that of tradables vs. nontradables, since the former are directly affected by the shock, whereas the latter only indirectly. Table 1.5 addresses this issue by splitting the sample between nontradable and tradable sectors.

As the top two panels of table 1.5 shows, the outline for the nontradable sector is very similar to that of the full sample, with almost no statistically significant coefficient – the exception now is the one for the effect of the import shock on the p50-p10 gap of residual wages, again positive and barely significant.

For the tradables sectors, however, the two bottom panels of table 1.5 present a very different picture for the effect of the export shock: the coefficients on all inequality measures but the p90-p50 gap are larger in magnitude, statistically significant, and all negative, pointing to a reduction in wage inequality as a consequence of the rise in Chinese demand for Brazilian products. The magnitudes are economically meaningful: an increase in export demand equivalent to the difference between the micro-regions in the 90th and 10th percentiles of exposure to the shock is associated with a decrease of 15% of a standard deviation of the overall 2010-2000 difference in the residual wage variance; the corresponding figures for the p90-p10 and p50-p10 wage gaps are 10% and 15%, respectively. The results for the import shock are once again imprecisely estimated.

The results presented in table 1.5 suggest that the reduction in wage inequality in the tradable sector due to the export shock was mainly concentrated in the lower part of the wage distribution: both the gap between the top and the bottom deciles and between the median and the first decile were compressed, while the p90-p50 is unaltered, pointing to a relative rise of lower wages *vis-à-vis* the rest of the distribution. This pattern is similar to what happened with the whole Brazilian wage distribution during that decade, as shown by Alvarez et al. (2018), for example.

Table 1.5: Effects of the China Shock on Inequality – Tradables vs. Nontradables

2010-00 difference in:	(1) Variance	(2) p90-p10 gap	(3) p90-p50 gap	(4) p50-p10 gap
Panel A: Nontradables, observed (log) wages				
Export Shock	0.001	0.015	0.015	0.002
	(0.006)	(0.013)	(0.011)	(0.005)
Import Shock	0.002	-0.006	-0.028	0.019
	(0.009)	(0.030)	(0.027)	(0.013)
R-squared	0.447	0.420	0.405	0.364
Observations	413	413	413	413
Panel B: Nontradables, residual wages				
Export Shock	-0.001	0.003	0.007	-0.004
	(0.003)	(0.008)	(0.007)	(0.003)
Import Shock	-0.006	-0.013	-0.024	0.013
	(0.007)	(0.022)	(0.020)	(0.007)*
R-squared	0.620	0.535	0.559	0.237
Observations	413	413	413	413
Panel C: Tradables, observed (log) wages				
Export Shock	-0.024	-0.033	-0.003	-0.024
	(0.009)**	(0.019)*	(0.018)	(0.010)**
Import Shock	-0.008	-0.005	0.008	-0.009
	(0.023)	(0.041)	(0.039)	(0.016)
R-squared	0.284	0.255	0.297	0.197
Observations	408	408	408	408
Panel D: Tradables, residual wages				
Export Shock	-0.017	-0.028	-0.013	-0.013
	(0.006)***	(0.013)**	(0.011)	(0.006)**
Import Shock	-0.002	0.002	0.014	-0.011
	(0.013)	(0.029)	(0.021)	(0.014)
R-squared	0.229	0.272	0.269	0.151
Observations	408	408	408	408

Notes: this table reports the effects of Chinese export and import shock on the 2010-2000 difference in measures of wage inequality at the micro-region level, for nontradables (panels A-B) and tradables (panels C-D). All columns report the results of 2SLS regressions where the regressands are measures of wage inequality, and the variables of interest are the micro-region-level measures of exposure to the China export and import shock, instrumented using measures of the excess contribution of China to the growth rate of world imports and exports (excluding Brazil) in a given sector, as described in section 1.2.2. "p90-p10" refers to the log ratio of the percentiles 90 and 10 of the wage distribution, and similarly for "p90-p50" and "p50-p10". Measures of inequality are calculated from observed wages (panels A and C) and from the residuals of Mincerian regressions including education, age, age squared, race, gender and state dummies (panel B and D). All specifications include State dummies and control for demographic characteristics of the micro-regions (shares of female workers and of high-school graduates in 1991) and for the 1991 level of the dependent variables. Standard errors (in parentheses) are clustered at the meso-region level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

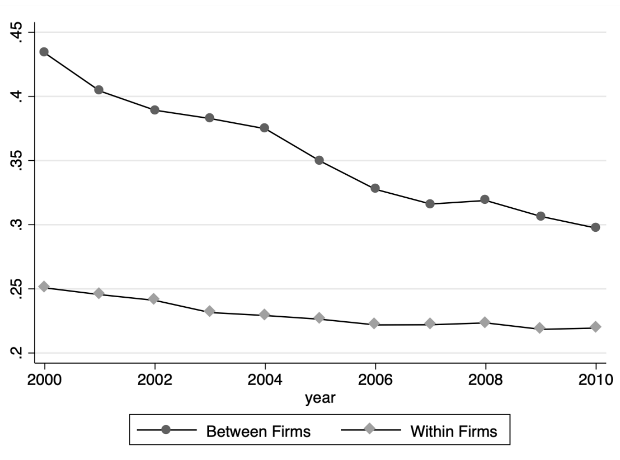
1.2.4.1 Wage Variance Decomposition

Next, we investigate the relationship between the trade shocks and the within-firm and between-firms components of wage variance. As Fortin et al. (2011) and Alvarez et al. (2018) show, denoting by y_{ijt} the (log) wage of worker i employed by firm j in period t, and by $\bar{y}_{jt}$ the average log wage in firm j, we can decompose the total variance in log earnings in two components:

$$Var(y_{ijt}) = Var(\bar{y}_{jt}) + \overline{Var(y_{ijt}|i \in j)} \tag{1-7}$$

The first term in the right-hand side of (1-7) is the between-firms component of wage variance – that is, the dispersion among firms' average wages. The second term is the within-firm component – the dispersion of wages among employees of a same firm. If, for example, firms tend to pay their workers homogeneously, but some firms pay much higher wages than others, the first component will dominate. If, on the contrary, firms tend to pay similar wages in average, but in a same firm some employees earn much higher wages than others, the second component will be responsible for most of the overall wage variance in the economy.

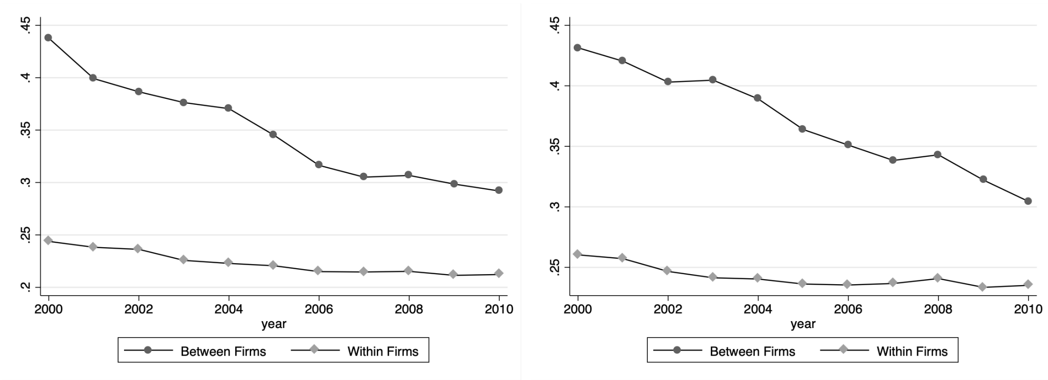
Figure 1.5: Evolution of Wage Variance Components



Source: Author's calculations from RAIS data

The plot in figure 1.5 suggests that, in Brazil, the behavior of firms resembled the first stylized case in the beginning of the XXIst century, but less so by the end of the decade: the between-firm component is higher along the whole decade, but even though both components have declined, the reduction in average wage dispersion between firms was much more pronounced than that in the within-firm component. Moreover, as figure 1.6 shows, this pattern can be observed both in tradables and in nontradable sectors.

Figure 1.6: Evolution of Wage Variance Components



Nontradables Tradables

Source: Author's calculations from RAIS data

These components, as well as the share of the total variance that is explained by the between-firm component, were then used as outcomes in regressions of the form in (1-3), to check how the China shock affected the wage-setting behavior of firms. The results are reported in table 1.6. The results for the total variance from table 1.4 are reproduced in column 1 for convenience.

As the table shows, no results were found for the effect of the export shock on whole RAIS sample (panels A and B) or on nontradables (panels C and D). This was expected, given that no discernible effects on total wage variance were found in tables 1.4 and top half of 1.5. As for the import shock, even though no effects were visible for the total wage variance, there seems to be an increase in the between-firm component in nontradables, which is also reflected in the full sample, especially for residual wages – and perhaps accompanied by a decrease in the within-firm component, which would explain the absence of effects on overall variance.

As for the tradables sectors (panels E and F of table 1.6), results show that the effect of the export shock in wage variance found in table 1.5 was completely driven by the between-firms component, whose estimates are almost identical to those of total variance; the coefficients for the effect on the within-firm component are very close to zero.

Table 1.6: Effects of the China Shock on Wage Variance Decomposition

2010-00 Difference in:	(1) Variance	(2) Share Var. Between Firms	(3) Var. Between Firms	(4) Var. Within Firms
Panel A: All Sectors, observed (log) wages				
Export Shock	-0.001	-0.001	0.000	-0.000
	(0.005)	(0.004)	(0.002)	(0.003)
Import Shock	-0.005	-0.015	0.013	-0.023
	(0.008)	(0.012)	(0.010)	(0.018)
Panel B: All Sectors, residual wages				
Export Shock	-0.002	-0.001	-0.001	-0.002
	(0.003)	(0.002)	(0.001)	(0.003)
Import Shock	-0.006	-0.011	0.008	-0.028
	(0.007)	(0.008)	(0.004)**	(0.015)*
Panel C: Nontradables, observed (log) wages				
Export Shock	0.001	0.000	0.000	-0.001
	(0.006)	(0.004)	(0.002)	(0.003)
Import Shock	0.002	-0.008	0.016	-0.017
	(0.009)	(0.011)	(0.008)*	(0.016)
Panel D: Nontradables, residual wages				
Export Shock	-0.001	-0.001	-0.000	-0.000
	(0.003)	(0.002)	(0.001)	(0.003)
Import Shock	-0.006	-0.010	0.009	-0.024
	(0.007)	(0.007)	(0.004)**	(0.014)*
Panel E: Tradables, observed (log) wages				
Export Shock	-0.024	-0.014	-0.024	0.002
	(0.009)**	(0.007)**	(0.009)***	(0.003)
Import Shock	-0.008	-0.003	-0.012	0.006
	(0.023)	(0.012)	(0.019)	(0.008)
Panel F: Tradables, residual wages				
Export Shock	-0.017	-0.014	-0.016	-0.001
	(0.006)***	(0.007)**	(0.005)***	(0.002)
Import Shock	-0.002	-0.019	-0.009	0.008
	(0.013)	(0.010)*	(0.009)	(0.006)

Notes: this table reports the effects of Chinese export and import shock on the 2010-2000 difference in the components of wage variance at the micro-region level, for all sectors (panels A-B), nontradables (panels C-D) and tradables (panels E-F). All columns report the results of 2SLS regressions where the regressands are components of wage variance, and the variables of interest are the micro-region-level measures of exposure to the China export and import shock, instrumented using measures of the excess contribution of China to the growth rate of world imports and exports (excluding Brazil) in a given sector, as described in section 1.2.2. “Var. Between Firms” refers to variance of average wages across firms, and “Var. Within Firms” to the variance of wages among workers of each firm. The variance components are calculated from observed wages (panels A, C and E) and from the residuals of Mincerian regressions including education, age, age squared, race, gender and state dummies (panel B, D and F). All specifications include State dummies and control for demographic characteristics of the micro-regions (shares of female workers and of high-school graduates in 1991) and for the 1991 level of the dependent variables. Standard errors (in parentheses) are clustered at the meso-region level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Taking Stock

To sum up the results so far, we have shown that the China export shock has contributed to the decline in wage inequality in tradables, leading to a significant reduction in wage variance and the 90-10 and 50-10 percentile gaps, both in observed log wages and in the residuals of a Mincerian regression. The effect on the percentile gaps suggest that the reduction in wage inequality has been driven by a rise in the bottom part of the wage distribution, which is consistent with findings in the literature. The import shock, however, had no discernible effects.

We have also presented evidence that the compression in tradables' wage dispersion due to the China export shock has operated mainly though the equalization of average wages between firms, and not through the reduction in wage variance among workers within a firm. This is also compatible with the literature, which shows that the between-firms component has been the main responsible for the reduction in wage variance in Brazil in the first decade of this century.

The fact that the between-firm component is solely responsible for the reduction in wage variance for tradables due to the export shock suggests that firms may have had a role in this process, which is also in line with the findings of Alvarez et al. (2018). It should be noted, however, that it not necessarily means that the reduction was driven by a change in firm behavior – that is, that high-paying (low-paying) firms decreased (increased) their average wages. This may also have been driven by composition, if the *size* of high-paying (low-paying) firms have decreased (increased) as a share of total employment, or if firms that are entering or exiting the market are concentrated in different sections of the wage distribution. The next section presents evidence on which of these hypotheses is more plausible.

1.2.5
Decrease in Between-Firm Wage Dispersion: Composition or Behavior

The last subsection has shown that the reduction in wage inequality in tradables due to the export facet of the China shock was driven mainly through the compression in average wage dispersion between firms – which is in line with findings that point to the between-firms component as the main responsible for the decline in wage inequality in Brazil in the 2000's, such as Alvarez et al. (2018). As noted, although this points to firms having a role in this reduction, it doesn't necessarily mean that a change in firm behavior was behind this, since composition effects could lead to similar results. In this subsection, we will present evidence that suggest that, instead of the latter, the former – high-paying firms decreasing their average wages, and/or low-paying ones increasing it – was the main responsible for the decline in average wage dispersion between firms.

1.2.5.1 Stayer vs. Other Firms

First, we look at changes in the composition of the pool of firms. The idea is to rule out firm entry or exit as a driver of the decline in wage dispersion – which could lead to the aforementioned composition effects. To do so, we split our sample between *stayer* firms (those that exist both in 2000 and 2010) and those that either are born or die between the two periods – that is, between the balanced panel and its complement – and run the main regressions from section 4.1 on the two subsets. Table 1.7 presents the results for the tradables sector [6].

Table 1.7: Results: Stayers vs. Other Firms (Tradables)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2010-00 diff. in:	Variance		p90-p10 gap		p90-p50 gap		p50-p10 gap	
Wage type:	Obs.	Resid.	Obs.	Resid.	Obs.	Resid.	Obs.	Resid.
Panel A: Stayer Firms								
Export Shock	-0.032	-0.020	-0.057	-0.042	-0.030	-0.027	-0.023	-0.015
	(0.014)**	(0.009)**	(0.028)**	(0.021)**	(0.026)	(0.018)	(0.012)*	(0.008)*
Import Shock	-0.010	-0.002	-0.018	0.009	0.021	0.028	-0.037	-0.018
	(0.017)	(0.009)	(0.030)	(0.020)	(0.028)	(0.018)	(0.019)*	(0.013)
Panel B: Other Firms								
Export Shock	0.005	-0.000	0.011	0.002	0.029	0.015	-0.015	-0.013
	(0.009)	(0.007)	(0.025)	(0.015)	(0.017)*	(0.010)	(0.015)	(0.009)
Import Shock	-0.003	0.005	0.050	0.020	-0.021	-0.021	0.069	0.041
	(0.038)	(0.020)	(0.055)	(0.046)	(0.062)	(0.036)	(0.038)*	(0.019)**

Notes: this table reports the effects of Chinese export and import shock on the 2010-2000 difference in measures of wage inequality at the micro-region level for tradables, restricting the sample to firms that exist both in 2000 and 2010 (panel A) and for firms that exist on either 2000 or 2010 (panel B). All columns report the results of 2SLS regressions where the regressands are measures of wage inequality, and the variables of interest are the micro-region-level measures of exposure to the China export and import shock, instrumented using measures of the excess contribution of China to the growth rate of world imports and exports (excluding Brazil) in a given sector, as described in section 1.2.2. "p90-p10" refers to the log ratio of the percentiles 90 and 10 of the wage distribution, and similarly for "p90-p50" and "p50-p10". Measures of inequality are calculated from observed wages (odd-numbered columns) and from the residuals of Mincerian regressions including education, age, age squared, race, gender and state dummies (even-numbered columns). All specifications include State dummies and control for demographic characteristics of the micro-regions (shares of female workers and of high-school graduates in 1991) and for the 1991 level of the dependent variables. Standard errors (in parentheses) are clustered at the meso-region level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[6] As in section 4.1, results for all and nontradable sectors are mostly insignificant, and therefore are ommitted for clarity.

As Table 1.7 clearly shows, the results from section 4.1 are mainly driven by the balanced panel (top panel), even though it comprises roughly one quarter of the total of firms that are present in both periods. Magnitudes are also similar to the main results: comparing a microregion in the 10th percentile of the export shock to one in the 90th percentile, the implied decreases in wage variance, 90-10 gap and 50-10 gap are roughly 23%, 20% and 15% (respectively) of a standard deviation in the overall 2010-2000 difference of each variable (in all cases the magnitudes are similar for observed and residual wages).

As for the complement of the balanced panel, the estimated coefficients are much smaller than their counterparts for the balanced panel, and mostly insignificant. This suggests that the results are largely driven by what happened to firms that exist in the whole period, as opposed to the impact of changes in the composition of the firm pool by new entrants or firm exit.

1.2.5.2
Firm-Level Wages

Next, we proceed to estimate the effects of the China shock on firm average wages. By doing so, we can examine if the shock has affected firm average wages in a more direct manner, which would also be suggestive of an effect on firm behavior. The procedure is identical to that of Section 4.1, except for the fact that instead of calculating the variance and percentile gaps of contract-level wages, we calculate these measures of inequality for the firm-level average of contracts[7].

Once again, for the full sample and for the nontradables sector (table A.8 in Appendix A.1) virtually all estimated coefficients are statistically insignificant. As for the tradables sector, if all firms are included (table 1.8, columns 1-4), only the effect of the export shock on wage variance is significant, while if only the balanced panel is considered (columns 5-8), the effect on the 90-10 and 90-50 gaps are also negative and significant. Magnitudes are relatively higher than those for contract-level wages: focusing on residual wages, and again comparing microregions in the 90th and 10th percentiles of shock intensity, the effect on variance and the 90-50 gap are around one third of a standard deviation of the overall 2010-2000 difference, while the figure for the 90-10 gap is approximately 40%.

In Appendix A.1, we examine the effects not on the gaps between percentiles but on the percentiles themselves – that is, on the 2010-2000 difference between the *values* of the 90th, 50th and 10th percentiles. Results

[7]In Appendix A.2 we present results using firm fixed effects in Mincerian wage equations as an alternative measure of firm-level wages, leading to similar conclusions.

show that, in consonance with the idea of a change in behavior of firms, the export shock has contributed to an increase in the wages of low-paying firms (that is, those in the percentile 10 of the average wage distribution) and a decrease in the wages of high-paying firms (percentile 90) in the tradables sector.

Table 1.8: Results using Firm Avg Wages – Tradables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Tradables							
	All Firms				Stayer Firms Only			
2010-00 diff. in:	Var.	p90-p10 gap	p90-p50 gap	p50-p10 gap	Var.	p90-p10 gap	p90-p50 gap	p50-p10 gap
Panel A: observed (log) wages								
Export Shock	-0.024	-0.042	-0.026	-0.010	-0.032	-0.097	-0.068	-0.022
	(0.009)***	(0.034)	(0.031)	(0.013)	(0.012)***	(0.037)***	(0.033)**	(0.018)
Import Shock	-0.012	-0.022	0.006	-0.023	-0.017	-0.076	-0.016	-0.057
	(0.019)	(0.042)	(0.060)	(0.028)	(0.015)	(0.037)**	(0.041)	(0.019)***
R-squared	0.261	0.189	0.179	0.189	0.260	0.211	0.214	0.207
Panel B: residual wages								
Export Shock	-0.016	-0.029	-0.019	-0.006	-0.019	-0.073	-0.053	-0.013
	(0.005)***	(0.024)	(0.025)	(0.007)	(0.007)***	(0.027)***	(0.022)**	(0.013)
Import Shock	-0.009	-0.063	-0.041	-0.021	-0.011	-0.077	-0.044	-0.030
	(0.009)	(0.039)	(0.040)	(0.018)	(0.007)	(0.040)*	(0.043)	(0.016)*
R-squared	0.203	0.192	0.167	0.143	0.182	0.197	0.183	0.169
Obs.	408	408	408	408	402	402	402	402

Notes: this table reports the effects of Chinese export and import shock on the 2010-2000 difference in measures of firm average wage inequality at the micro-region level for tradables, restricting the sample to firms that exist both in 2000 and 2010 (columns 1-4) and for firms that exist on either 2000 or 2010 (columns 5-6). All columns report the results of 2SLS regressions where the regressands are measures of wage inequality, and the variables of interest are the micro-region-level measures of exposure to the China export and import shock, instrumented using measures of the excess contribution of China to the growth rate of world imports and exports (excluding Brazil) in a given sector, as described in section 1.2.2. "p90-p10" refers to the log ratio of the percentiles 90 and 10 of the wage distribution, and similarly for "p90-p50" and "p50-p10". Measures of inequality are calculated from firm-level averages of observed wages (panel A) and of the residuals of Mincerian regressions including education, age, age squared, race, gender and state dummies (panel B). All specifications include State dummies and control for demographic characteristics of the micro-regions (shares of female workers and of high-school graduates in 1991) and for the 1991 level of the dependent variables. Standard errors (in parentheses) are clustered at the meso-region level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Also in Appendix A.1, we repeat the previous exercise separately for firms that change their position in the wage distribution between 2000 and 2010, and for those who stay in the same average wage quintiles during the whole period. Results suggest that movement of firms along the average wage distribution may play a role: while the effect on the bottom of the distribution seems to be driven by firms that change their position in the average wage distribution, the top part appears to be affected by the firms that stay in the same quintiles.

1.2.5.3
Effects on Employment of Firms by Average Wage Percentiles

We now proceed to examine whether the China shocks have affected differently the employment of firms in different parts of the wage distribution. The main purpose here is to check if the decrease in between-firms wage inequality may be due to a composition effect, that is, an increase in the employment of low-paying firms or an decline in that of high-paying firms. The dependent variable is now the employment share of firms in the neighborhood of each of the selected percentiles of the wage distribution. Table 1.9 displays the results for the balanced panel; the top panel orders firms according to the distribution of observed log wages, while the bottom one considers that of residual wages.

As the top panel of table 1.9 shows, the export shock has led to an increase in employment share of high-paying firms in tradables, and a reduction in employment of firms in the middle portion of the distribution for nontradables. The implied magnitudes are not negligible: again comparing microregions in the 90th and 10th percentiles of shock intensity, the effect on tradables' p90 is around 15% of a standard deviation of the overall difference, while the corresponding figure for the negative effect on p50 in nontradables is 13% of a SD. The import shock seems to have affected only nontradables, and particularly the bottom part of the distribution, with similar magnitude (10% of a standard deviation for the 10th percentile). Results focusing on log employment instead of employment shares (presented in table A.3 in Appendix A.1) tell a similar story.

In the bottom panel, however, most estimates are much smaller than those of the top panel and statistically insignificant. That is, when firms are ranked according to the residual wage distribution – the portion of wages not explained by observables – the employment effects virtually vanish.

The results presented in table (1.9) focus on the employment of firms in each portion of the wage distribution, attributing firms to percentiles according to each year's distribution. That is, we compare the employment shares of, say, high paying firms in 2000 with that of high-paying firms in 2010, which may or may not be the same firms – even though the set of firms is the same in both years, there could have been movement of firms along the wage distribution between the two years. Thus, next we examine whether this movement of firms along the average wage distribution contributes to the results, or these are driven by employment changes in the same firms.

Table 1.9: Effects on Employment Share by Avg. Wage Percentiles – Stayer Firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		All Sectors			Nontradables			Tradables	
2010-00 diff. in:	p90	p50	p10	p90	p50	p10	p90	p50	p10
Panel A: employment share of pctile of observed (log) wages									
Export Shock	0.004	-0.005	-0.002	0.003	-0.006	-0.001	0.020	-0.004	0.004
	(0.004)	(0.002)**	(0.002)	(0.003)	(0.002)***	(0.002)	(0.007)***	(0.003)	(0.003)
Import Shock	0.009	-0.003	0.006	0.004	-0.004	0.008	-0.017	-0.003	-0.003
	(0.009)	(0.006)	(0.003)**	(0.007)	(0.004)	(0.003)**	(0.014)	(0.008)	(0.005)
R-squared	0.149	0.117	0.287	0.150	0.159	0.297	0.102	0.078	0.114
Panel B: employment share of pctile of residual wages									
Export Shock	-0.003	-0.001	-0.001	-0.006	-0.002	-0.001	0.009	-0.003	0.000
	(0.004)	(0.002)	(0.001)	(0.004)	(0.002)	(0.001)	(0.007)	(0.003)	(0.002)
Import Shock	0.006	-0.001	0.002	0.004	0.005	0.003	-0.033	0.011	0.002
	(0.009)	(0.004)	(0.004)	(0.007)	(0.008)	(0.005)	(0.020)*	(0.008)	(0.006)
R-squared	0.132	0.134	0.070	0.143	0.133	0.090	0.158	0.108	0.061
Observations	413	413	413	413	413	413	402	402	402

Notes: this table reports the effects of Chinese export and import shock on the 2010-2000 difference in employment shares of firms in the neighborhood of selected percentiles of the firm average wage distribution. All columns report the results of 2SLS regressions where the regressands are differences in employment shares, and the variables of interest are the micro-region-level measures of exposure to the China export and import shock, instrumented using measures of the excess contribution of China to the growth rate of world imports and exports (excluding Brazil) in a given sector, as described in section 1.2.2. "p90", "p50" and "p10" refer to percentiles 90, 50 and 10 of the firm-level average wage distribution. Firms are ranked according to their position in the distribution of firm-level average observed wages (panel A), and of firm-level averages of the residuals of Mincerian regressions including education, age, age squared, race, gender and state dummies (panel B). All specifications include State dummies and control for demographic characteristics of the micro-regions (shares of female workers and of high-school graduates in 1991) and for the 1991 level of the dependent variables. Standard errors (in parentheses) are clustered at the meso-region level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The first way to do this is to simply assign firms to percentiles of the wage distribution in the base year and examine the difference in average wages practiced by these firms between the two years. That is, instead of comparing, for example, the average wages of high-paying firms in 2000 to that of high-paying firms in 2010, we compare the average wages of 2000's high-paying firms in 2000 to that of these same firms in 2010. Results are presented in tables A.5 and A.4 in Appendix A.1 and show that virtually all the effects vanish, suggesting that the effects on employment are mainly driven by the movement of firms along the average wage distribution.

Another way of assessing the role of the movement of firms along the average wage distribution is to divide each sample in two subsets: the *movers* (the firms that occupied a different quintile of the 2010 wage distribution than the one it occupied in the 2000 wage distribution) and the *non-movers* (the firms that are in the same quintile in the both years' wage distributions, which comprise approximately 5% of the total[8]).

[8]More and less strict definitions of movers and non-movers – considering deciles and

Table 1.10: Firms that Change Avg. Wage Quintile vs. Firms that Stay in Avg. Wage Quintile

2010-00 diff. in:	(1) All Sectors p90	(2) All Sectors p50	(3) All Sectors p10	(4) Nontradables p90	(5) Nontradables p50	(6) Nontradables p10	(7) Tradables p90	(8) Tradables p50	(9) Tradables p10
Panel A: Employment Share of Firms that Change Observed Wage Quintiles									
Export Shock	0.007	-0.009	-0.002	0.007	-0.009	-0.000	-0.007	-0.014	0.001
	(0.005)	(0.004)**	(0.003)	(0.003)**	(0.004)**	(0.003)	(0.008)	(0.006)**	(0.004)
Import Shock	-0.019	-0.003	0.006	-0.017	-0.002	0.008	0.014	-0.014	-0.021
	(0.009)**	(0.008)	(0.004)	(0.009)*	(0.007)	(0.005)*	(0.016)	(0.012)	(0.021)
R-squared	0.109	0.134	0.329	0.097	0.192	0.366	0.103	0.090	0.164
Obs.	413	413	413	413	413	413	399	399	399
Panel B: Employment Share of Firms that Change Residual Wage Quintiles									
Export Shock	-0.003	0.000	-0.002	0.001	-0.002	-0.002	0.005	-0.006	0.000
	(0.004)	(0.003)	(0.001)*	(0.005)	(0.003)	(0.001)	(0.008)	(0.006)	(0.003)
Import Shock	-0.001	0.008	0.007	0.002	0.007	0.008	-0.023	0.020	0.006
	(0.012)	(0.008)	(0.006)	(0.010)	(0.010)	(0.008)	(0.019)	(0.014)	(0.007)
R-squared	0.073	0.109	0.061	0.130	0.127	0.091	0.146	0.184	0.060
Obs.	413	413	413	413	413	413	399	399	399
Panel C: Employment Share of Firms that Stay in Observed Wage Quintiles									
Export Shock	-0.001	0.002	-0.000	-0.004	-0.002	-0.002	0.004	-0.004	-0.003
	(0.006)	(0.002)	(0.001)	(0.006)	(0.002)	(0.001)*	(0.010)	(0.004)	(0.002)
Import Shock	-0.008	-0.001	0.007	0.011	0.007	0.011	-0.006	0.009	0.026
	(0.011)	(0.006)	(0.003)**	(0.013)	(0.005)	(0.009)	(0.023)	(0.009)	(0.015)*
R-squared	0.122	0.103	0.088	0.087	0.106	0.105	0.155	0.107	0.064
Obs.	409	409	409	409	409	409	374	374	374
Panel D: Employment Share of Firms that Stay in Residual Wage Quintiles									
Export Shock	-0.006	0.001	-0.000	-0.006	-0.001	-0.001	0.010	-0.004	-0.001
	(0.006)	(0.002)	(0.001)	(0.007)	(0.002)	(0.001)	(0.010)	(0.004)	(0.002)
Import Shock	0.021	-0.003	-0.004	0.011	-0.003	-0.004	0.001	0.020	0.006
	(0.015)	(0.007)	(0.002)**	(0.012)	(0.006)	(0.002)*	(0.020)	(0.013)	(0.008)
R-squared	0.104	0.116	0.059	0.089	0.148	0.048	0.184	0.106	0.071
Obs.	409	409	409	409	409	409	374	374	374

Notes: this table reports the effects of Chinese export and import shock on the 2010-2000 difference in employment shares of firms in the neighborhood of selected percentiles of the firm average wage distribution, restricting the samples to firms that occupied a different quintile of the 2010 distribution than the one it occupied in the 2000 distribution (panels A-B), and to firms that occupied the same quintile in both years (panels C-D). All columns report the results of 2SLS regressions where the regressands are differences in employment shares, and the variables of interest are the micro-region-level measures of exposure to the China export and import shock, instrumented using measures of the excess contribution of China to the growth rate of world imports and exports (excluding Brazil) in a given sector, as described in section 1.2.2. "p90", "p50" and "p10" refer to percentiles 90, 50 and 10 of the firm-level average wage distribution. Firms are ranked according to their position in the distribution of firm-level average observed wages (panel A), and of firm-level averages of the residuals of Mincerian regressions including education, age, age squared, race, gender and state dummies (panel B). All specifications include State dummies and control for demographic characteristics of the micro-regions (shares of female workers and of high-school graduates in 1991) and for the 1991 level of the dependent variables. Standard errors (in parentheses) are clustered at the meso-region level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Results (table 1.10) suggest a less clear picture. It is not clear which subsample is the main driver of the positive effect of the export shock on high-wage tradables firms, since no significant effects were found. As for nontradables, the effects of the export shock seem driven by the firms that

terciles of the wage distribution, respectively – yield similar results.

change average wage quintiles: their estimate on panel A of table 1.10 have the same signs of their counterparts in table 1.9 and the magnitudes are similar, while in panel C of table 1.10 the only visible effects of the export shock on nontradables are on the lower part of the wage distribution, smaller in magnitude than the other ones and significant only at the 10% level. Similarly, the effect of the import shock on the percentile 10 for nontradables also seems driven by the firms that change quintiles.[9]

Taking Stock

To sum up, we argue that the evidence presented in this section is consistent with the hypothesis that the effect of the export shock on tradables wage variance (that works through the between-firm variance) is due to changes in firm behavior, and not by composition.

First, results hardly change if we restrict the sample to the balanced panel – that is, if we rule out changes in the composition of the firm pool, which suggests that firm entry or exit hasn't been a driver in the decline in wage dispersion.

Second, there is evidence that the China export shock has affected firm average wages directly: we have found significant effects of the shock on inequality measures calculated from the firm-level average wage distribution, particularly if we focus only on the balanced panel of firms that are present both in 2000 and 2010. We also find evidence that the effects are at least partly driven by the movement of firms along the distribution of average wages, especially the increase in wages of low-paying firms.

Finally, the evidence suggests that the decrease in between-firm dispersion of wages does not seem driven by the composition of employment between high- and low-paying firms. In fact, there is hardly any effect of the export shock on employment of firms in different parts of the average wage distribution – if anything, there may have been an increase in the employment of high-paying firms.

1.2.6
Mechanism: Effects on Exporter Wage Premium

In the previous subsections, we discussed a set of results that pointed to the export-demand side of the China shock as having contributed to the reduction in wage inequality in the tradables sector. Moreover, we have presented suggestive evidence that this effect manifested itself through the

[9]The effects on log employment, also available in Appendix A.1, are similar.

between-firms component of wage dispersion, and that it has stemmed from changes in firm behavior, rather than composition effects.

In this subsection, we will dig deeper in examining a possible mechanism underlying these effects, focusing on the behavior of exporter firms. There is ample evidence in the literature pointing to the fact that firms that engage in exporting activities are typically larger, more productive, and pay higher wages than those that are confined to serving the domestic market (see, for example, Bernard et al. (2007)). In this subsection, we focus on the relationship between the China shock and the wage premium paid by exporter firm, using the same empirical strategy as in the previous ones.

It should be noted that other candidate mechanisms were also investigated, with broadly negative and inconclusive results. For example, we haven't found any visible effects of the China export shock on the skill composition of the labor force or in the return to these observable characteristics; neither on firm dynamics, such as entry, exit or hiring. Appendix A.3 discusses these (non-)results.

The exporter wage premium at the micro-region level was obtained as the coefficient for an interaction term between an exporter firm indicator[10] and micro-region dummies in Mincerian regressions at the contract level, which also include indicators for each tradable sector[11] and control for (log) firm employment. That is, the coefficient capture the premium payed by exporter firms *vis-à-vis* non-exporter firms of similar size, in the same sector and micro-region. Evidently, the analysis in this subsection focuses on tradables sectors.

Results in table 1.11 point to a negative effect of the export shock on the exporter wage premium. The magnitude of the effect is substantial: comparing one micro-region in the 90th percentile of shock exposure with one in the 10th percentile, the implied effect corresponds to more than half of the average 2000 level of the micro-regions' exporter wage premium. The import shock has no visible effect.

As before, the effect is similar if the sample is restricted to the balanced panel of firms that are present on RAIS in 2000 and 2010, as shown in the second column of table 1.11. Similarly, the results are broadly maintained if we consider as exporter firms only those which export across the entire period (that is, both in 2000 and 2010), as illustrated in column 3; if, on the contrary, we consider only firms that were exporters only in one of those years (ie either firms that became exporters between 2000 and 2010, or that ceased exporting

[10]The analysis therefore is restricted to the extensive margin – ignoring the intensive margin of export activity – due to data constraints.

[11]The main specification considers three sectors: manufacturing, mining and agriculture. Adopting a more disaggregated sector definition (two-digit CNAE) yields similar results.

activity in this period), the estimated effect of the export shock is smaller, less precise, and lose statistical significance, suggesting that the decline in wage premium is driven by firms that engage in exporting activity throughout our time frame. Moreover, if we split the sample into high- and low-paying firms – defined as those with firm average residual wage above and below median, respectively –, the corresponding results (columns 3 and 4 of table 1.11) suggest that the reduction in the exporter wage premium is driven by the former; for the latter, the estimated effect is positive in sign, although significant only at the 10% level[12].

Table 1.11: Exporter Wage Premium

	(1)	(2)	(3)	(4)	(5)	(6)
	2010-2000 Difference in Exporter Wage Premium					
	All Firms	Stayers	Always exporters	New/Former exporters	High-Paying Stayer Firms	Low-Paying Stayer Firms
Export Shock	-0.028	-0.031	-0.038	0.014	-0.041	0.028
	(0.012)**	(0.011)***	(0.016)**	(0.016)	(0.012)***	(0.015)*
Import Shock	-0.040	-0.010	-0.005	0.041	-0.040	0.027
	(0.024)*	(0.025)	(0.024)	(0.024)*	(0.038)	(0.026)
Obs.	375	367	340	335	365	250
R-squared	0.193	0.158	0.191	0.159	0.190	0.265

Notes: this table reports the effects of Chinese export and import shock on the 2010-2000 difference in the wage premium of exporter firms. All columns report the results of 2SLS regressions where the regressands are exporters' wage premium, and the variables of interest are the micro-region-level measures of exposure to the China export and import shock, instrumented using measures of the excess contribution of China to the growth rate of world imports and exports (excluding Brazil) in a given sector, as described in section 1.2.2. The wage premium is obtained as the coefficient of an exporter firm dummy on Mincerian regressions including education, age, age squared, race, gender, firm size, and sectoral and state dummies. Columns 2-6 restrict the sample to (respectively): firms that exist both in 2000 and 2010; firms that are exporters both in 2000 and 2010; firms that exist both in 2000 and 2010 but export only in one of the years; firms that exist both in 2000 and 2010 and have above-median average wages; and firms that exist both in 2000 and 2010 and have below-median average wages. All specifications include State dummies and control for demographic characteristics of the micro-regions (shares of female workers and of high-school graduates in 1991) and for the 1991 level of the dependent variables. Standard errors (in parentheses) are clustered at the meso-region level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Next, we examine the effects on the employment of exporter firms. As

[12]One possible concern with the results on restricted samples – especially in the case of insignificant results – arises from the reduced number of observations, which follows from the fact that some micro-regions do not contain firms that fulfill the selection criteria of the subsample; for example, some micro-regions have no exporter firms, or no high-paying firms. Results could then be biased due to sample selection, or simply have large standard errors because of the smaller sample, causing the statistical insignificance. To alleviate these concerns, the same regressions for all firms were ran restricting the samples to the smaller sets of micro-regions in which there are high or low paying firms. Results (presented in Appendix A.2.3) are broadly the same as those obtained with the whole sample; in particular, this corroborates the conclusion that the absence of negative results for new/former exporters and for low-paying firms are indication that the reduction in exporter wage premium is mainly driven by firms that always export, and by firms with above-median average wages

the results in table 1.12 show, there is a negative effect of the export shock on the total employment of exporter firms – although the effect on the log of employment is insignificant, suggesting that the effect may be driven by the behavior of outliers; the latter interpretation is reinforced by the fact that there is no effect on exporter firms' share in total employment. There is also a positive effect of the export shock on the average employment of exporter firms, although the relative magnitude of the effect is small: the comparison among the 90th and 10th percentiles of shock exposure is equivalent to about 5% of the average micro-region level on 2000.

Table 1.12: Employment in Exporter Firms

2010-2000 Diff. in:	(1) Exporter Employment	(2) Exporter Log Employment	(3) Share Emp. Exporters	(4) Avg. Exporter Employment
Panel A: All Firms				
Export Shock	-1,714.515	-0.011	0.009	0.772
	(762.286)**	(0.058)	(0.006)	(0.367)**
Import Shock	8,131.560	0.380	0.063	2.086
	(3,131.900)***	(0.150)**	(0.017)***	(1.811)
Observations	409	409	409	409
R-squared	0.824	0.205	0.239	0.087
Panel B: Stayers				
Export Shock	-1,256.459	-0.019	0.009	2.656
	(681.805)*	(0.069)	(0.007)	(1.017)***
Import Shock	6,174.120	0.194	0.039	4.689
	(3,072.237)**	(0.112)*	(0.020)**	(6.027)
Observations	403	403	403	403
R-squared	0.927	0.203	0.237	0.294
Panel C: Always Exporters				
Export Shock	-1,062.281	0.076	0.003	1.620
	(514.039)**	(0.044)*	(0.008)	(0.812)**
Import Shock	5,137.963	0.093	0.014	2.547
	(2,687.185)*	(0.110)	(0.017)	(4.867)
Observations	403	403	403	403
R-squared	0.911	0.164	0.179	0.343

Notes: this table reports the effects of Chinese export and import shock on the 2010-2000 difference in measures of employment of exporter firms. All columns report the results of 2SLS regressions where regressands are the measures of employment, and the variables of interest are the micro-region-level measures of exposure to the China export and import shock, instrumented using measures of the excess contribution of China to the growth rate of world imports and exports (excluding Brazil) in a given sector, as described in section 1.2.2. The wage premium is obtained as the coefficient of an exporter firm dummy on Mincerian regressions including education, age, age squared, race, gender, firm size, and sectoral and state dummies. Panel B restricts the sample to firms that exist both in 2000 and 2010, and panel C to firms that are exporters both in 2000 and 2010. All specifications include State dummies and control for demographic characteristics of the micro-regions (shares of female workers and of high-school graduates in 1991) and for the 1991 level of the dependent variables. Standard errors (in parentheses) are clustered at the meso-region level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Results also point to a positive effect of the import shock on exporter employment and on the share of the micro-region's workforce employed in exporter firms; again, however, the magnitudes are small, with the same comparison amounting to less than one tenth of the 2000 mean levels.

In order to further examine the heterogeneous effects on exporter and non-exporter firms, we calculate the same moments of the firm average wage distribution as in table 1.8, but now dividing the sample between exporter and non-exporter firms. One first observation that emerges from the results (illustrated in table 1.13) is that the effects of the export shock on firm average wage variance and on the gap between percentiles 90 and 10, which were mostly negative and precisely estimated when all firms were considered, are now mostly insignificant. This suggests that the decrease in wage dispersion could be in part driven by an approximation of the wage distributions of exporter and non-exporter firms, which would be consistent with the decline in the wage premium payed by exporters[13].

Another result that is visible in table 1.13 is the negative effect of the export shock on the p50-p10 gap for exporter firms, which is very precisely estimated and large in magnitude: again comparing micro-regions in the 90th and 10th percentiles of shock exposed, the implied effect is equivalent to half a standard deviation in the decline of this moment of the wage distribution between 2000 and 2010, both when observed and residual wages are considered[14]. This suggests that the aforementioned compression in the lower portion of the wage distribution, discussed in the previous section, may be emerging from the effect on exporter firms. Moreover, when we further restrict the sample to include only the firms that were exporters in both years, we also find a positive effect on the wage gap between the 90th and 50th percentiles.

In Appendix A.1, we also investigate whether the distinct effects of the export shock on exporters and non-exporters may be related to changes in the skill composition of the workforce employed by these two subsets of firms, as well as in the returns to observable measures of worker skill (we consider three

[13]As discussed in the previous footnote, one could be concerned that this absence of significant results could stem from the restricted sample size; to alleviate these potential concerns, once again the same regressions were ran for all firms but reducing the sample to include only the micro-regions that have exporting firms, and also with only those with non-exporting firms. In both cases, results (displayed in tables A.2.3 and A.2.3 in Appendix A.2.3), are reassuringly similar to those in table 1.8, which suggests that the lack of results for the samples restricted by firm exporting status is not due to the limited number of observations, and instead corroborates the idea that the reduction in wage dispersion caused by the export demand shock is at least partly driven by the exporting status channel.

[14]A similar effect, although less precisely estimated, is obtained for the contract-level wage distribution of exporter firms, as shown in Appendix A.2.

levels: less than high-school, high-school and college graduates). No visible effects of the trade shocks on skill composition of exporter firms were obtained. As for non-exporting firms, there is a positive and statistically significant effect of the export shock on high-school graduates; the magnitude of the effect, however, is modest, comprising only 7% of the initial average level if we compare the 90th and 10th percentiles of shock exposure.

Table 1.13: Inequality Measures: Exporters vs. Non-Exporters

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2010-00 diff. in:	Variance		p90-p10 gap		p90-p50 gap		p50-p10 gap	
Wage type	Observed	Residual	Observed	Residual	Observed	Residual	Observed	Residual
Panel A: Exporters								
Export Shock	-0.007	-0.009	-0.045	-0.059	0.055	0.012	-0.101	-0.074
	(0.014)	(0.008)	(0.047)	(0.032)*	(0.042)	(0.024)	(0.026)***	(0.019)***
Import Shock	-0.025	-0.017	-0.010	-0.070	-0.045	-0.049	0.042	-0.015
	(0.022)	(0.012)	(0.077)	(0.058)	(0.066)	(0.052)	(0.043)	(0.033)
Obs	274	274	274	274	274	274	274	274
R-squared	0.390	0.325	0.512	0.407	0.516	0.432	0.353	0.317
Panel B: Always Exporters								
Export Shock	0.004	-0.005	0.024	-0.011	0.103	0.054	-0.084	-0.068
	(0.018)	(0.010)	(0.044)	(0.036)	(0.034)***	(0.022)**	(0.035)**	(0.030)**
Import Shock	-0.015	-0.010	-0.020	-0.045	-0.092	-0.038	0.076	0.004
	(0.024)	(0.014)	(0.059)	(0.048)	(0.051)*	(0.046)	(0.050)	(0.038)
Obs.	235	235	235	235	235	235	235	235
R-squared	0.498	0.316	0.548	0.421	0.596	0.516	0.285	0.245
Panel C: Non-Exporters								
Export Shock	-0.002	-0.004	0.018	0.010	0.039	0.027	-0.016	-0.011
	(0.006)	(0.004)	(0.021)	(0.015)	(0.019)**	(0.016)*	(0.012)	(0.009)
Import Shock	0.002	0.003	0.011	0.001	0.029	0.010	-0.019	-0.013
	(0.007)	(0.004)	(0.017)	(0.020)	(0.033)	(0.021)	(0.028)	(0.022)
Obs.	404	404	404	404	404	404	404	404
R-squared	0.211	0.148	0.218	0.159	0.190	0.151	0.207	0.205

Notes: this table reports the effects of Chinese export and import shock on the 2010-2000 difference in measures of wage inequality at the micro-region level for tradables, restricting the sample to firms that export in 2000 or 2010 (panel A), firms that export in 2000 and 2010 (panel B), and to firms that never export (panel C). All columns report the results of 2SLS regressions where the regressands are measures of wage inequality, and the variables of interest are the micro-region-level measures of exposure to the China export and import shock, instrumented using measures of the excess contribution of China to the growth rate of world imports and exports (excluding Brazil) in a given sector, as described in section 1.2.2. "p90-p10" refers to the log ratio of the percentiles 90 and 10 of the wage distribution, and similarly for "p90-p50" and "p50-p10". Measures of inequality are calculated from observed wages (odd-numbered columns) and from the residuals of Mincerian regressions including education, age, age squared, race, gender and state dummies (even-numbered columns). All specifications include State dummies and control for demographic characteristics of the micro-regions (shares of female workers and of high-school graduates in 1991) and for the 1991 level of the dependent variables. Standard errors (in parentheses) are clustered at the meso-region level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The export shock seems to have increased the college premium and decreased the return to experience in exporting firms, although these effects almost disappear when we look to the balanced panel. Among non-exporters, there is a positive effect of the export shock on the high-school premium, which is precise but of similar magnitude than the effect on the share of high-school graduates.

In sum, while the effects on exporter firms are less clear, there is evidence that the export shock has increased both the share and the return of high-school graduates in non-exporting firms. However, while this may have contributed to the compression in the exporter wage premium, the relative magnitudes of both seem rather small, which puts into question whether it was a significant driving force of this effect.

Taken together, the results of this subsection point to a compression of the exporter wage premium as a possible mechanism contributing to the effect of the China export shock on wage inequality. In light of these results, the next section examines this potential relationship between external demand, the exporter wage premium and wage inequality using the structural framework developed by Helpman et al. (2017), in which exporter firms tend to be more productive and invest more in screening its workforce for unobservable skill components, leading to the existence of inequality among ex-ante identical workers.

1.3 Foreign Demand, Exporter Wage Premium and Wage Inequality

In the previous section, we have presented a series of reduced-form evidence on the relative effects of the China shock across micro-regions, part of which can be summarized as follows: (i) the foreign demand induced by the rise of China affected each sector in different ways, and it has led to a decline in the dispersion of wages in the tradables sectors; (ii) this reduction has worked mainly through the between-firms component of wage dispersion, rather than the within-firm component; (iii) it seems to have been driven by firm behavior, rather than composition effects; (iv) this change in behavior appears to be related to the compression in the exporter wage premium – that is, although exporter firms on average pay higher wages across the whole period, this higher wage conditional on firm exporting status seems to have been negatively affected by the external demand shock. The purpose of this section is to examine this relationship between foreign demand, the exporter wage premium, and wage inequality in a more general context than that of comparing micro-regions, so as to shed light on the overall effects of the China shock in the whole economy.

To do so, we employ the structural framework developed by Helpman, Itskhoki, Muendler and Redding (2016, hereafter referred to as HIMR), which contains a number of features that makes it suitable to this task: it features firm heterogeneity and fixed costs of exporting *à la* Melitz (2003) – which leads to differences in firm productivity conditional on exporting status –, but also incorporates matching frictions and unobserved match-specific component of worker productivity, resulting in differences not only in productivity but also in wages conditional on exporting status, and leads to wage inequality between workers that are *ex ante* identical on observables – which is consistent with the existence of dispersion in residual wages examined in the previous section.

Unlike HIMR, however, we do not focus on trade costs in our counterfactual exercise; instead, we explore sectoral-level differences in the foreign demand shock, which affected distinctly across sectors the evolution of the ratio of foreign to domestic demand – a central variable in the structural model, which determines key parameters in the econometric model –, to examine if this variable alone can explain part of the observed aggregate reduction in the exporter wage premium and in wage dispersion.

1.3.1 Structural Framework

In this and the following subsections, we briefly describe the framework developed by HIMR; a more detailed description is available in Appendix A.4. We begin by describing the structural model, and in the next section we describe the steps that HIMR take obtain a log-linearized econometric version of the model, as well as the relationship between the parameters and shocks in the ecometric model and how they relate to their structural counterparts.

The structural model consists of a set of sectors populated by a large number J of firms j producing differentiated varieties and supplying two markets, domestic (d) and export (x), under monopolistic competition. In each country there is a continuum of workers that are observationally identical, and which have Constant Elasticity of Substitution (CES) preferences over the sector's varieties. As HIMR show, the model's predictions for wages and employment across firms within a given sector are independent of general equilibrium effects, so that we can focus on one sector only.

The production technology of each firm depends on its productivity θ, the measure of workers it employs h, and the average ability of it's workforce $\bar{a}$; parameter restrictions ensure that there is complementarity between firm and (average) worker productivity[15], which, as noted, will be central in establishing

[15]Helpman et al. (2010) show that a production technology with this feature can be derived

the key result that more productive firms – exporters in particular – will typically pay higher wages.

The exporting activity involves both a fixed cost $e^{\epsilon}F_x$ (with a firm-specific component ϵ) and an iceberg variable cost τ. Given these costs, a firm will decide if it will serve the foreign market and, if it does, it will allocate its output between the two markets in order to maximize revenue. This allows for expressing total firm revenue $r(j)$ as a function of its total output, a domestic demand shifter A_d, an indicator of its export status ι, and a *market access* variable Υ_x that summarizes the effect on a firm's revenue of accessing the export market, and depends on *relative external demand* $A \equiv \frac{A_x}{A_d}$ and the variable trade cost:

$$r(j) = [1 + \iota(\Upsilon_x - 1)]^{1-\beta} A_d y(j)^{\beta} \tag{1-8}$$

where $\Upsilon_x = 1 + \tau^{\frac{-\beta}{1-\beta}} A^{\frac{1}{1-\beta}}$.

From (1-8), we can notice the effect of exporting on firm revenue: a firm that does not access the foreign market faces the revenue function $r(j) = A_d y(j)^{\beta}$. If it becomes an exporter, however, its revenue shifts to $r(j) = \Upsilon_x^{1-\beta} A_d y(j)^{\beta}$; since $\Upsilon_x^{1-\beta}$ is strictly larger than one, it represents the revenue premium earned by the firm that decides to sell in the foreign market – this decision, as will be better detailed ahead, will crucially depend on whether this increase in revenue offsets the fixed cost that the firm must pay to engage in exporting activity.

The ability level a of an individual worker is is Pareto-distributed and *ex ante* unobservable, both for the worker and for the firms. Labor markets exhibits Diamond-Mortensen-Pissarides model search and matching frictions. After matching, even though a firm still cannot identify precisely the ability level of each of its workers, it screens them to detect and lay off those with ability below a threshold level a_c; this screening activity involves a cost that is increasing in the threshold level. Thus, by screening and not hiring workers with productivity below a stipulated level, the firm is able to increase the average productivity of its workforce; given the complementarity between firm productivity and workers' average ability, more productive firms will have more incentive to be more rigid in their screening policies, and therefore will tend to have workforce with higher average ability. A more stringent screening policy will also come at the cost of reducing the measure of workers actually hired.

by assuming either that human capital exhibits complementarity between each worker and the team she is in, or that production teams are led by a manager who has to allocate a fixed amount of time among the workers under her command.

Wages are set through a Stole-Zwiebel multilateral bargaining process, which results in the firm receiving a constant fraction of revenue, and all workers in a firm earning the same wages. Moreover, given that wages are a constant fraction of firm revenue, more productive firms will tend to pay higher wages, and exporting firms will on average pay higher wages than a non-exporting firm, even if we condition on productivity and size – in other words, part of the revenue premium earned by exporter firms is transferred to the workers in the bargaining process, and becomes the *exporter wage premium*[16].

The solution to the firm's problem, as described in Appendix A.4, result in four main equilibrium conditions that illustrate a key feature of the model, which is the two-sided nature of the relationship between firm characteristics and the decision to export. There is a *selection effect*: high productivity firms, which tend to be larger and pay higher wages, are also more likely to become an exporter, since its revenue premium is more likely to be large enough to cover the fixed cost. But there is also the *market access effect*, in which accessing the export market boosts firm revenue, thus increasing firm employment and wages – the result is that exporter firms will tend to have higher average wages even after controlling for other firm characteristics such as productivity and size.

The latter effect is at the root of the exporter wage premium as understood in the last section; thus, in the next subsection we will show how HIMR use the structure of the model to derive an estimable econometric model that is able to identify these two mechanisms, and in the following one we use the estimated parameters to perform a counterfactual exercise designed to examine how the rise in China could have affected the relative external demand A across sectors, and its effects on the exporter wage premium and on wage inequality.

1.3.2 Econometric Model

To obtain an estimable model, HIMR derive a log-linearized econometric version of the structural framework presented in the previous subsection. As shown in Appendix A.6, by taking logs of the structural equilibrium conditions of the model we'll obtain[17]:

[16] It should be noted, however, that neither of these relationships – which will manifest themselves on data as positive correlations between productivity, size, revenue, and wages, as well as higher average revenue and wages for exporters conditional on size – are perfect, due to the existence of firm-specific components of both screening and fixed export costs.

[17] Is is important to notice that, apart from the theoretical structure described here, this econometric model is also consistent with a host of other structural models that feature selection into exporting and equilibrium firm wages that increase with revenues or profits,

$$\begin{aligned} \log(h) &= \alpha_h + \mu_h \iota + u && (1\text{-}9) \\ \log(w) &= \alpha_w + \mu_w \iota + \zeta u + v && (1\text{-}10) \\ \iota &= \mathbb{I}\{z \geq f\} && (1\text{-}11) \end{aligned}$$

where $log(h)$ and $log(w)$ are natural logarithms of firm employment and wages, respectively; $\mathbb{I}\{.\}$ is an indicator function; (u, v, z) are linear transformations of the structural shocks (θ, η, ϵ), as detailed in Appendix A.6; and $(\alpha_h, \alpha_w, \mu_h, \mu_w, \zeta, f)$ are combinations of variables and parameters of the structural model, also defined in the Appendix.

In particular, the coefficients (μ_h, μ_w, f) are central to our counterfactual, since the first two capture the effect of export-led enhanced market access on employment and wages, while the latter is the exporting decision threshold; moreover, (μ_h, μ_w, f) are directly affected by the central variable of the counterfactual, the relative external demand A:

$$\begin{aligned} \mu_h &= \frac{\delta - k}{\delta} \log\left(\Upsilon_x^{\xi_1}\right) && (1\text{-}12) \\ \mu_w &= \frac{k}{\delta} \log\left(\Upsilon_x^{\xi_1}\right) && (1\text{-}13) \\ f &= \frac{1}{\sigma}\left[-\alpha_\pi + \log(F_x) - \log\left(\Upsilon_x^{\xi_1} - 1\right)\right] && (1\text{-}14) \end{aligned}$$

where α_π and σ are combinations of parameters, also defined in Appendix A.6. Recalling that $\Upsilon_x = 1 + \tau^{\frac{-\beta}{1-\beta}} A^{\frac{1}{1-\beta}}$, one can notice that an increase in A will expand the export revenue premium, and therefore push up the effect of exporting on employment and wages (increasing μ_h and μ_w) and pull down the bar for entry into exports (reducing f). By the same token, a reduction in A will shrink the revenue premium and the market access coefficients (μ_h, μ_w), and push up the threshold f.

To obtain an estimable model, we assume that the structural shocks (θ, η, ϵ) are jointly normally distributed, which implies joint normality of the combined shocks (u, v, z):

$$(u, v, z) \sim \mathcal{N}(\mathbf{0}, \Sigma), \quad \Sigma = \begin{bmatrix} \sigma_u^2 & 0 & \rho_u \sigma_u \\ 0 & \sigma_v^2 & \rho_v \sigma_v \\ \rho_u \sigma_u & \rho_v \sigma_v & 1 \end{bmatrix} \qquad (1\text{-}15)$$

such as other models with competitive assortative matching (as Sampson (2014)) or fair wage models (as Egger and Kreickemeier (2012)).

The next section will discuss the estimation of the vector of coefficients $\Theta = \{\alpha_h, \alpha_w, \mu_h, \mu_w, \zeta, f, \rho_u, \rho_v, \sigma_u, \sigma_v\}$.

1.3.3 Estimation and Model Fit

As detailed in Appendix A.6, the econometric model admits a likelihood function given by $\mathcal{L}(\Theta|x_j) \equiv \prod_j \mathbb{P}_\Theta\{x_j\}$, where

$$\mathbb{P}_\Theta\{x_j\} = \frac{1}{\sigma_u}\phi(\hat{u}_j)\frac{1}{\sigma_v}\phi(\hat{v}_j)\left[\Phi\left(\frac{f-\rho_u\hat{u}_j-\rho_v\hat{v}_j}{\sqrt{1-\rho_u^2-\rho_v^2}}\right)\right]^{1-\iota_j}\left[1-\Phi\left(\frac{f-\rho_u\hat{u}_j-\rho_v\hat{v}_j}{\sqrt{1-\rho_u^2-\rho_v^2}}\right)\right]^{\iota_j}$$

in which ϕ and Φ are the density and distribution of a standard normal, $\hat{u}_j \equiv (h_j - \alpha_j - \mu_h\iota_j)/\sigma_u$, and $\hat{v}_j \equiv [(w_j - \alpha_w - \mu_w\iota_j) - \zeta\sigma_u\hat{u}_j]/\sigma_v$. Notice that the first two first terms in the right-hand side are determined by the distribution of the two reduced-form shocks, while the two last terms comprise a Probit of the export status given firm employment and wages.

The model was estimated separately by sector, for 2000 and 2010. As will be detailed in the next subsection, this sectoral-level estimation is key for the counterfactual exercise. The preferred disaggregation level considers 13 sectors[18]. Table 1.14 displays the minimum, average and maximum estimates across sectors of each of the parameters of interest, as well as the results of an estimation aggregating all sectors; the full set of estimates and standard errors for each sector is presented in Table A.47, in Appendix A.8.

Table 1.14: Model Estimates (Aggregate and by Sector)

Param.	Point Estimates (2000)				Point Estimates (2010)			
	All Sectors	Sectoral Min	Sectoral Mean	Sectoral Max	All Sectors	Sectoral Min	Sectoral Mean	Sectoral Max
μ_h	2.32	1.60	2.17	3.04	2.18	1.50	2.08	2.87
μ_w	0.18	0.08	0.18	0.29	0.15	0.08	0.16	0.25
ρ_u	0.03	-0.09	0.05	0.19	0.07	0.00	0.08	0.19
ρ_v	0.25	-0.03	0.24	0.43	0.27	0.08	0.23	0.38
f	1.66	1.07	1.54	1.95	1.74	1.02	1.61	2.02

[18]The sectors are: Agriculture, forestry and Fishing; Mining; Food, Beverages and Tobacco; Textiles, Leather and Apparel; Wood, Paper and Printing; Chemical Products; Plastic and Rubber; Non-Metallic Minerals; Primary and Fabricated Metals; Machinery; Computer and Electronics; Transport Equipment; and Furniture and Manufactures n.e.s. The Petroleum and Coal sector was excluded from the main estimation due to the small number of observations; results including this sector are similar to the main results, and are presented in Appendix A.8.

Estimates are broadly compatible with those obtained by HIMR[19], albeit with some sectoral variation. Almost all estimates are statistically significant at the 1% level; the only exceptions are the estimates of ρ_u for four sectors in 2000 and three in 2010, which are not indistinguishable from zero. In particular, the market access parameters μ_h and μ_w are all positive and statistically significant, as the structural parameter restrictions would imply – it should be noted that this assumption was not imposed as a constraint in the maximization of the likelihood function. Thus, as expected, entry into exporting raises employment and wages in all sectors. Selection parameters ρ_u and ρ_v are almost all positive also, which means that for most sectors the firms that engage in exporting activities are those with higher wages and larger workforces[20].

In order to examine the fit of the model, we simulated an artificial dataset using the estimated parameters, aggregating sectors according to their relative size in the actual data. We then calculated a set of firm- and worker-level moments for this dataset and actual data; the results are detailed in Appendix A.7.

The quality of the model fit is similar to the one obtained in HIMR; the model fits very well the firm-level moments for all firms and for non-exporters, although it underestimates the dispersion of employment and its correlation with wages. As for the workers' level dispersion of wages, the model seems to fit well the standard deviation, even though it performs differently in different portions of the wage distribution. Moreover, the model emulates fairly well changes across time in the differentials between wage percentiles. The model is also capable of capturing the relationship between firm-level wages, firm employment and export status that is present in the data.

In sum, although not perfect in some cases, these results show that the model is able to fit fairly well a set of moments of the wage distribution that were not targeted in the estimation, including less trivial ones such as the gaps between wage percentiles. In the next subsection, we use the estimated parameters for the base year to perform a counterfactual exercise that aims to capture the interrelationship between external demand, the exporter wage premium, and wage inequality.

[19]For reference, the baseline estimates obtained by HIMR are $\mu_h = 1.99$, $\mu_w = 0.20$, $\rho_u = 0.02$, $\rho_v = 0.20$ and $f = 1.34$.

[20]The one notable exception is the Wood, Paper and Printing sector, in which the estimates for ρ_u were insignificant in both years, and those for ρ_v were barely negative for 2000 and positive but much smaller than most sectors in 2010.

1.3.4 Counterfactual Exercise

As discussed in Section 1.2, the reduced-form evidence suggest that the foreign demand shock induced by the rise of China as a major player in international trade caused simultaneously a reduction in the wage dispersion in tradable sectors and a decline in the wage premium paid by exporter firms. We now use the parameter estimates from the last subsection to perform a counterfactual exercise to examine the interplay between these factors in a controlled setting consistent with the structural framework developed by HIMR and described in this section. The main question that underlies this exercise can be stated as follows: "can the distinct sectoral pattern of the evolution of relative foreign demand driven by Chinese expansion explain at least part of the reduction, observed in aggregate data, in the exporter wage premium and in wage inequality?" To do so, we begin by estimating the sector-level China-led variation in relative foreign demand (A), and then calculate counterfactual 2010 values for the econometric model parameters by changing solely the underlying value of A – that is, the counterfactual 2010 parameter values assume that everything except relative foreign demand stayed constant in the 2000 levels, and that A evolved in the trajectory driven by Chinese demand. We then build a "counterfactual 2010" aggregate dataset, and compare the differences between this counterfactual data and the model-generated data for 2000 with the differences between model-generated data for 2010 and 2000 for a set of moments of the wage distribution. Our goal is to examine whether by changing only this parameter the model is able to emulate the observed trend in the exporter wage premium and in wage inequality.

To obtain sector-level estimates of the Chinese impact on relative domestic demand, we followed a procedure inspired by the instrumental variables approach adopted in Section 1.2. We re-estimated the auxiliary regressions used in the instrumental variables to obtain the excess contribution of China to the growth of exports in each of the 13 sectors, and used the estimates $\psi_{China,i}$ as instruments in a first-stage regression of the observed change in A, the predicted values of which were used as the counterfactual measure of the China-led variation in relative domestic demand[21]. These estimates were then used to obtain the counterfactual values of μ_h, μ_w and f, and a counterfactual 2010 dataset was constructed using these and the 2000 estimates of the remaining parameters.

[21] The estimated coefficient for the first stage regression is 0.18, significant at the 1% level, with a R-squared of 0.29 and a F-statistic equal to 11.42.

Table 1.15: Counterfactual Results: Aggregate Dataset

	Model 2000	Model 2010	% Dif from Baseline	Counter-factual	% Dif from Baseline
Fraction of exporters	0.051	0.043	-14.5%	0.046	-9.7%
Size premium	0.074	0.067	-9.0%	0.077	3.6%
Exporter premium	0.239	0.214	-10.6%	0.222	-7.3%
St. Dev. log worker wage					
— All Firms	0.470	0.385	-18.1%	0.432	-8.2%
— Non-Exporters	0.401	0.326	-18.7%	0.403	0.7%
— Exporters	0.446	0.357	-19.9%	0.452	1.5%
90-10 ratio	3.315	2.681	-19.1%	2.983	-10.0%
90-50 ratio	1.894	1.711	-9.7%	1.777	-6.1%
50-10 ratio	1.751	1.567	-10.5%	1.678	-4.1%

Table 1.15 report the results. The first two columns display the moments of the artificial datasets built with actually estimated parameters, for the baseline year (2000) and for 2010, while the third presents the percent difference between 2010 and 2000. The results of the counterfactual exercise are presented in the fourth column: these are the moments of the artificial dataset generated with counterfactual values of the parameters that are affected by A, while keeping the remaining coefficients at the 2000 level. Finally, the fifth column displays the percent difference between this "counterfactual 2010" moments and their baseline 2000 values.

Comparing columns 3 and 5 of table 1.15, one can notice that by varying solely the relative foreign demand A, the model is able to emulate about two thirds of the decline in the share of exporter firms and in the exporter premium that are obtained when all parameters are allowed to change; the size premium, however, almost doesn't change in the counterfactual.

As for the wage dispersion, the change in relative foreign demand A explains about half of the reduction in standard deviation when all firms are considered; this decline seems to be relatively well distributed across the wage distribution, as the behavior of the percentile wage gaps suggest. Interestingly, in the counterfactual, there is almost no change in wage dispersion compared to the baseline when either exporters or non-exporters are focused at. This is in line with the reduced-form results presented in table 1.13, in which we show that the effect of the export shock on wage inequality almost vanishes when we separate firms according to exporting status; once again, we conclude that this evidence is suggestive that at least part of the effect of the foreign demand shock on wage inequality was driven by the relationship between exporter and non-exporter firms.

Table 1.16: Counterfactual Results: Sectors

	Model		% Dif from	Counter-	% Dif from
	2000	2010	Baseline	factual	Baseline
Panel A: Agriculture					
Fraction of exporters	0.035	0.022	-38.2%	0.033	-5.6%
Size premium	0.040	0.061	51.4%	0.039	-2.6%
Exporter premium	0.164	0.118	-27.9%	0.172	5.1%
St. Dev. log worker wage					
— All Firms	0.428	0.361	-15.6%	0.419	-2.1%
— Non-Exporters	0.419	0.347	-17.3%	0.414	-1.2%
— Exporters	0.411	0.342	-16.8%	0.412	0.3%
90-10 ratio	2.964	2.521	-14.9%	2.923	-1.4%
90-50 ratio	1.736	1.600	-7.8%	1.710	-1.5%
50-10 ratio	1.708	1.575	-7.8%	1.710	0.1%
Panel B: Mining					
Fraction of exporters	0.050	0.045	-9.4%	0.049	-2.2%
Size premium	0.111	0.118	6.3%	0.113	2.5%
Exporter premium	0.134	0.181	35.2%	0.145	8.7%
St. Dev. log worker wage					
— All Firms	0.464	0.443	-4.7%	0.452	-2.7%
— Non-Exporters	0.443	0.402	-9.1%	0.444	0.3%
— Exporters	0.424	0.394	-7.2%	0.446	5.2%
90-10 ratio	3.267	3.131	-4.2%	3.178	-2.7%
90-50 ratio	1.796	1.781	-0.9%	1.783	-0.7%
50-10 ratio	1.819	1.759	-3.3%	1.782	-2.0%
Panel C: Manufacturing					
Fraction of exporters	0.052	0.045	-12.7%	0.046	-10.4%
Size premium	0.076	0.064	-15.6%	0.079	3.3%
Exporter premium	0.236	0.218	-7.5%	0.221	-6.5%
St. Dev. log worker wage					
— All Firms	0.466	0.383	-17.9%	0.426	-8.6%
— Non-Exporters	0.393	0.319	-18.8%	0.396	0.9%
— Exporters	0.440	0.356	-19.1%	0.442	0.5%
90-10 ratio	3.293	2.651	-19.5%	2.948	-10.5%
90-50 ratio	1.899	1.702	-10.4%	1.777	-6.5%
50-10 ratio	1.734	1.558	-10.2%	1.659	-4.3%

Finally, table 1.16 shows that, as expected, these aggregate results are driven by sector-level results that vary widely. For ease of exposition, the 11 manufacturing sectors are lumped together in panel C of table 1.16; the results are predictably similar to aggregate ones. As for the agriculture and mining sectors, the behavior is considerably different. For the former, the counterfactual result shows a moderate increase in exporter wage premium, compared with a very large decrease obtained when all the parameters change; the effect on wage inequality measures is very small in the counterfactual, in contrast to the much larger decline in estimated data. For the mining sector, we also obtained a moderate counterfactual increase in the exporter wage premium, but the estimated results point to a large increase; the measures of inequality point to a qualitatively similar behavior to that of manufactures, albeit with much smaller time variation.

1.4 Concluding Remarks

This paper examines the effects of the "China shock" – the sharp increase in both import supply and export demand due to the emergence of China as a major player in international trade – on Brazilian labor market, in particular on measures of wage inequality, using two empirical approaches.

In the first part of the paper, we exploit variation in exposure across local labor markets to obtain reduced-form evidence on these effects. We follow Costa et al. (2016) and account for endogeneity by instrumenting the evolution of bilateral trade between Brazil and China with a counterfactual trajectory based on a measure of Chinese push on global trade. The evidence gathered suggests that the export-demand side of the China shock may have contributed to the reduction in wage inequality in the tradables sector. Moreover, we present suggestive evidence that this effect manifested itself through the between-firms component of wage dispersion, and that it has stemmed from changes in firm behavior, rather than composition effects. We also show that this change in behavior appears to be related to a compression in the exporter wage premium – that is, although exporter firms on average pay higher wages across the whole period, this higher wage conditional on firm exporting status seems to have been negatively affected by the external demand shock.

To circumvent the inherent limitation posed by this empirical strategy – which can only provide information on the relative effects across regions on the within-region inequality –, in the second part of this paper we employ a structural framework developed by Helpman et al. (2017) to further examine the relationship between foreign demand, the exporter wage premium, and wage inequality. We estimate a log-linearized version of the model and perform counterfactual exercises exploring sectoral-level differences in the foreign demand shock, which affected distinctly across sectors the evolution of the ratio of foreign to domestic demand, to show that this variable alone – that is, the China demand shock – can explain part of the observed aggregate reduction in the exporter wage premium and in wage dispersion.

2
Trade and Labor Market Dynamics: Evidence from the China Shock on Brazil

2.1
Introduction

One of the earliest and most disseminated rationales for the relevance of international trade is the fact that it allows countries to allocate their resources more efficiently: instead of being forced to produce everything domestically, a country can focus on goods it produces more efficiently and trading part of its production with other nations, in exchange for other goods it may also want to consume but is not able to produce with the same competence. The obvious but sometimes overlooked flipside to this is that engaging in foreign trade will lead to a reshuffling of resources inside the economies: labor and capital that used to be dedicated to producing the less efficient items will then be made idle, and will have to seek employment elsewhere – possibly in the more efficient production, which will increase. The result, in the textbook frictionless environment, is an increase in total welfare, but things get more complicated if there are impediments to movement of resources between productive processes. The fact that there exists a thriving research agenda dedicated to studying distributional effects of trade suggests that these impediments indeed exist.

The rise of China as a major trading power in the global arena, following political and economic reforms initiated in the 1970s, have led to a massive reshuffling of resources around the world. The Asian giant's thriving manufacturing competitiveness has flooded most countries with goods "made in China", which led to the notion that manufacturing jobs everywhere were being exported to the far east. On the other hand, Chinese demand for raw materials have helped spur a boom in agricultural and mineral commodities trade in the early XXIst century. This development has gathered immense attention, and led to a growing concern for the effects of the "China trade shock" on labor markets of other countries. This paper adds to this research effort, by focusing on the effects of the rise of China on Brazilian labor markets.

In order to analyze the effects of the China shock on the dynamics of Brazilian labor market, we use a version of the multi-country, multi-sector general equilibrium framework developed by Caliendo et al. (2019). The model's rich structure incorporates features such as intermediate consumption, input-output linkages between sectors, productivity differentials at the country and firm levels, nontradable sectors and mobility costs that preclude immediate adjustment of the labor force in the face of price and wage changes, all of which are extremely relevant from an empirical standpoint. We extend the model to allow for heterogeneity in worker skill, by assuming that firms combine skilled and unskilled labor into a composite labor factor. This allows for analyzing the relative demand for both types of labor and distributional effects of the China shock without taking strong assumptions regarding, for example, the degree of substitutability between each type of labor and other inputs, as in Parro (2013).

Estimating a model with so many dimensions could be unfeasible; building on the work of Dekle et al. (2008), Caliendo et al. (2019) show how to rewrite the model in terms of time differences and ratios of time differences, so that many of the model fundamentals cancel out, and the model can be simulated – and counterfactual exercises performed – without the need to estimate a huge set of parameters.

The model features a dynamic discrete choice problem of labor supply based in Artuç et al. (2010), in which families choose the sector in which they will seek employment, taking into account wages, mobility costs, and an idiosyncratic preference component. In each period of the dynamic problem, wages are set through a static multi-sector Eaton-Kortum model with input-output linkages developed by Caliendo and Parro (2015).

The model is calibrated to a global input-output system developed by the World Input-Output Database (WIOD) Project (Timmer et al. (2015)) and a rich administrative dataset on Brazilian labor market, which allows for tracking worker transitions across sectors. We then use the calibrated model to perform counterfactual exercises simulating the push on Brazilian exports and imports led by the rise of China on global markets. Specifically, the main counterfactual scenarios are built by imposing changes in the growth of Chinese sectoral productivity so that the changes in bilateral trade between Brazil and China in each sector matches the estimates obtained in a first stage similar to that used in Chapter 1 – that is, a measure of bilateral trade growth in each sector that purges both local and global shocks, and is driven solely by the Asian giant.

The evidence suggests that both faces of the China shock – that is, the push on import supply and export demand driven by productivity growth in China – have contributed to the decline of manufacturing employment in Brazil in the first decade of this century, and that services sectors have absorbed most of the displaced workforce. Looking separately at each shock, the import shock has also increased employment in mining and decreased in agriculture, as well as in the residual "sector" that lumps unemployment and informality, while the export shock has driven an increase in both commodities sectors (as one might have expected). However, overall the effects are modest, especially in the export shock – which, given the nature of the model, operates mainly via input-output linkages and is partly offset by Chinese expansion as well.

In order to put these modest effects into perspective, an alternative counterfactual scenario was performed so as to emulate the reprimarization of Brazilian export basket through shocks in local productivity of the commodities sectors. Doing so, we are able to simulate the magnitude of the resource redistribution that would take place in the case of a trade shock that could drive a similar effect on total Brazilian exports. The results of this alternative counterfactual suggest that even in the case of export demand, the China shock is not enough to explain a significant part of the reshuffling of resources into commodities sectors.

The results also suggest that distributional effects of the China shock are small, but consistent with reduced-form evidence obtained in Chapter 1, with the import shock reducing the share of unskilled workers in the nontradables sectors and increasing in the tradables sectors, and the export shock leading to an even smaller effect on the relative demand for labor types.

This chapter contributes to a large literature that studies the labor market effects of the rise of China as a major trading power – a sizeable portion of which is dedicated to analyzing and quantifying its impacts on employment dynamics in the United States, such as Autor et al. (2013) and Pierce and Schott (2016), for example. Costa et al. (2016) and Pessoa and Costa (2020) focus on Brazil, and points out that for commodity-exporting countries the rise of China wasn't only a negative import competition shock, but also a positive export demand shock stemming from the Asian giant's growing appetite especially for agricultural and mineral goods. We contribute to this literature by providing evidence that is anchored in a dynamic structural model of trade and occupational choice, which allows us to consider explicitly the role of labor market and trade frictions, as well as general equilibrium effects on the labor market as a whole, thus complementing the reduced-form evidence that focuses on differential effects across regions or sectors.

On a methodological level, this chapter is closely related to an extensive literature focused on the labor market effects of trade shocks, especially one strand that models labor market decisions as a dynamic choice problem in an environment with mobility frictions. In particular, the choice framework for labor supply embedded in the model that underlies the analysis in this sector follows Artuç et al. (2010) in introducing idiosyncratic shocks to labor market preferences as modeled by Cameron et al. (2007) – without, however, allowing for unobserved heterogeneity in these preferences, as in Dix-Carneiro (2014). Caliendo et al. (2019) builds on Artuç et al. (2010), but adopts a much richer trade model than the simpler model considered by the latter, developing a multi-country, multi-sector general equilibrium framework which guides the empirical analysis in this chapter. Our contribution in this regard is to extend the model in Caliendo et al. (2019) to allow for heterogeneity in worker characteristics, namely in skill (as measured by educational attainment), so as to be able to shed light on distributional issues across workers of different skill levels.

The framework adopted here is also related to a strand of Ricardian trade models which extend Eaton and Kortum (2002) to include more realistic and empirically-focused features such as multiple sectors – as in Arkolakis et al. (2012), Chor (2010), Costinot et al. (2012) and Eaton et al. (2016) for example – and, most importantly, intermediate consumption and input-output linkages as in Caliendo and Parro (2015). These inter-sectoral relationships between producers in multiple sectors is crucial to the estimation of the effects of the China shock on labor markets.

This chapter is organized as follows. The next section briefly describes the model and the heterogeneous-labor extension, and discusses the solution method. Section 3 describes the data and calibration, as well as the counterfactual scenarios. Section 4 describes the results obtained in the counterfactual exercises. The final section presents the concluding remarks.

2.2 Theory

This section describes the heterogeneous labor extension to the theoretical model developed by Caliendo et al. (2019) and to the solution method proposed by the authors, which they denominate “dynamic hat algebra”. In a nutshell, the model combines a dynamic occupational choice structure and one static trade model at each period. The occupational choice block consists in forward-looking households that choose the sector in which they prefer to work, given equilibrium wages, fixed mobility costs, and a time-variable stochastic idiosyncratic preference component for sectors; distributional assumptions for this idiosyncratic shock give rise to a sequence of sectoral labor transition matrices which determine, in a given period, the fraction of workers in each sector that will move to each other sector (or stay in the same sector). The sequence of static problems, in turn, will determine equilibrium wages in each period; it is an EK-inspired multi-sector model in which firms in each sector in every country use as inputs goods from all sectors – in other words, the model features input-output linkages. As in Eaton and Kortum (2002), firms will source a product variety from the lowest-cost supplier, which will in turn depend on bilateral trade costs and on each producer's productivity. The latter has two components: one is time-varying but sector-country specific (and will be, as discussed forward, the engine through which the "China shock" works in the counterfactual exercises), while the other is variety-specific but stochastic; the distribution of this latter component will engender a gravity-like bilateral trade structure. At each period, given allocations, the solution to the trade model will result in a vector of wages and prices on which the occupational choice of families will be based.

One evident limitation of this framework is the absence of any dimension of heterogeneity in the labor force, which precludes any analysis of distributional effects of the trade shocks using this model. We therefore extend the model in order to introduce one kind of heterogeneity, namely, between "skilled" and "unskilled" workers – defined as those with and without a high school diploma, respectively.

In order to keep things simple, we assume that firms use both kinds of labor together in a "composite labor" input, which combines the two via a CES aggregator. This simple form will obviously mean that the implied distributional effects are limited, since they arise solely from the fact that sectors use each labor type in different intensities (which will be dictated by the data in our empirical application); however, it has the advantage of being "agnostic", in the sense that almost any other underlying hypothesis for the way in which firms combine the two types of labor – for example, assuming different elasticities of substitution between each type of labor and other inputs such as capital – will directly influence the effects of the trade shocks in the counterfactual exercises. Therefore, since examining the validity and empirical adequacy of such hypotheses is outside the scope of this paper, we leave for future work the use of more complex – and possibly more interesting – hypotheses, such as the one in Parro (2013), which uses a two-level aggregator which may imply the presence of capital-skill complementarity in production.

The next two subsections briefly describe the structural model and the solution method, focusing on the modifications to the original Caliendo et al. (2019) framework; a more detailed derivation is presented in Appendix B.1.

2.2.1
The Model

The structural framework adopted in this paper is an extension of Caliendo et al. (2019) (henceforth CDP), that combines a dynamic structure of sectoral workforce mobility based in Artuç et al. (2010) (henceforth ACM) to a multi-sector Eaton-Kortum trade model with input-output linkages developed by Caliendo and Parro (2015). The model considers also the possibility of trade deficits, which is key to its empirical application with real-world data. The main difference between the model used in this paper and the original framework developed by CDP is the presence of skill heterogeneity: we assume that there are two types of labor, unskilled (U) and skilled (S), which are supplied by the households to intermediate goods producers, that combine the two types into a CES labor aggregate. Another difference is the absence of an intra-national regional dimension: while CDP considers each of the 50 US states as different geographical units, this is not feasible for Brazil, given the absence of sufficiently detailed data on trade between Brazilian states for the period covered by this study.

The model considers J sectors (indexed by j or k) and N countries (indexed by n or i). Time is discrete and, each period, households in a given country (which have perfect foresight) choose optimally the sector in which they will work[1], taking into account the cost they incur in changing sectors (which is fixed in time) and a time-variable idiosyncratic preference component for sectors, as in ACM.

Each sector features a competitive labor market, and a *continuum* of firms producing intermediate goods in a perfectly competitive environment, by combining the two types of labor with structures (which is a input analogous to physical capital) and inputs from all sectors in a Cobb-Douglas production function with stochastic productivity, which follows (as in EK) a Fréchet distribution with dispersion parameter θ^j (which is the same for all firms in a given sector). In each country, all varieties of a given sector – acquired from wherever it can be supplied with the lowest cost (including the burden of bilateral trade costs) – are combined in a sectoral aggregate good, which is used both as final consumption and as input in the production of varieties in all sectors[2].

[1]The model abstracts from international migration.

[2]To grasp the difference between varieties and local aggregates, consider as example one sector from the empirical application below, such as "textiles, footwork and apparel". In this case, varieties may include textiles (such as fibers), apparel items, leather products, or shoes, for example. Each purchased "unit" of an aggregate good from this sector is a bundle of such varieties, which may be used as final consumption or as intermediate input to produce other varieties from this or other sectors.

Households

Households are forward looking and discount future consumption at rate $\beta \geq 0$. Each household is endowed with only one type of labor, U or S, and cannot change it (that is, we abstract from endogenous human capital decisions). Households with either type of labor have identical consumption preferences defined over a Cobb-Douglas aggregate of local final goods.[3]

At each period t, a household may be employed in one of the J sectors – supplying inelastically one unit of it's kind labor $l \in \{U, S\}$ in return for the competitive wage $w^j_{l,t}$, and therefore with its consumption level given by her real wages, $C^j_t = w^j_{l,t}/P_t$, where $P_t = \prod_{k=1}^J (P^k_t/\alpha^k)^{alpha^k}$ is the ideal price level implied by the aggregator C^j_t – or unemployed, in which case its consumption will be equal to $b > 0$, a parameter that may be interpreted either as unemployment insurance or as domestic subsistence production[4] (in order to simplify the notation, unemployment is denoted as the sector 0.

Households of a given type start each period in a given sector (including the sector 0 that denotes unemployment), earn the income associated to this sector, observe wages and prices in each sector, and discover the value of their idiosyncratic sectoral preference shock, ϵ^j_t – which distribution is Type I Extreme Value with zero average. Given these information, they decide whether or not to change their sector in the next period; in order to move from sector j to sector k they incur in a cost equal to $\tau^{j,k}$, which is constant in time and measured in utility units.

Thus, there are now two sequences of labor allocations – one for each labor type –, which, as shown in Appendix B.1, are fully described by the following equations:

$$U^j_{t+1} = \sum_{k=0}^{J} \mu^{j,k}_{u,t} U^k_t \quad \text{and} \quad S^j_{t+1} = \sum_{k=0}^{J} \mu^{j,k}_{s,t} S^k_t \tag{2-1}$$

where $\mu^{j,k}_{l,t}$ is the fraction of households of type l that decide to move from sector j to sector k[5]. Since households choose their sector optimally, they will move to sector k if their continuation value (net of costs) in k is larger than that of every other sector (including that of their current sector). Therefore, $\mu^{j,k}_t$ can be interpreted as the probability that the expected utility in k is the

[3]Note that even though households consume only local final goods, these are produced using inputs sourced from all countries; thus, international trade is key in this model.

[4]As it will be detailed ahead, data constraints will force us to lump unemployment and informality in the empirical application, in which case b may also be interpreted as informal labor income

[5]Notice that this notation includes those that decide to continue in the same sector, $\mu^{j,j}_t$.

largest among all sectors, and, as shown in B.1, the properties of the Type I Extreme Value distribution allows us to express it as:

$$\mu_{l,t}^{j,k} = \frac{\exp(\beta V_{l,t+1}^{k} - \tau^{j,k})^{\frac{1}{\nu_l}}}{\sum_{h=0}^{J} \exp(\beta V_{l,t+1}^{h} - \tau^{j,h})^{\frac{1}{\nu_l}}} \tag{2-2}$$

where $V_{l,t}^{j} \equiv E[v_{l,t}^{k}]$ the expected utility of a representative type-l household employed in sector j. That is, *ceteris paribus*, sectors with higher future expected utility (net of mobility costs) will attract more workers, with a mobility elasticity given by $1/\nu_l$.

Production of Intermediate Goods

In each country n, a set of firms in each sector produce varieties of intermediate goods, using labor l_t^{nj}, structures h_t^{nj} (a production factor which is analogous to physical capital but has a fixed supply[6] equal to H^{nj}), and sectoral aggregate inputs acquired from all sectors. The composite labor index l_t^{nj} is obtained by combining the two types of labor, u_t^{nj} and s_t^{nj}, through a Constant Elasticity of Substitution aggregator with elasticity of substitution given by σ, and a sector-specific share parameter δ^{nj}:

$$l_t^{nj} = \left[(\delta^{nj})^{\frac{1}{\sigma}}(u_t^{nj})^{\frac{\sigma-1}{\sigma}} + (1-\delta^{nj})^{\frac{1}{\sigma}}(s_t^{nj})^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$$

Intermediate goods production, as in CDP, follows a Cobb-Douglas function with constant returns to scale and two productivity components: a sectoral one (A_t^{nj}), which varies across time but is the same for all firms in that sector, and a firm-specific term (z^{nj}, which is also used to index varieties), which is fixed in time but stochastic, following a Fréchet distribution with dispersion parameter θ^j.

The solution to the intermediate producer's problem implies that the unit price of an input bundle x_t^{nj} is determined by intermediate input prices P_t^{nk}, the rental price of structures r_t^{nj} , and an agregate labor cost index w_t^{nj} which is a weighted sum of unskilled ($w_{u,t}^{nj}$) and skilled ($w_{s,t}^{nj}$) wages, given by:

$$w_t^{nj} = \left[\delta^{nj}(w_{u,t}^{nj})^{1-\sigma} + (1-\delta^{nj})(w_{s,t}^{nj})^{1-\sigma}\right]^{\frac{1}{1-\sigma}} \tag{2-3}$$

[6]That is, the model features "capital" in the production function, but abstracts from capital accumulation.

Given the perfectly competitive environment, local unit price in country n of a given variety will be determined by the lowest unit cost (trade costs included) across all countries that can produce that variety. Trade costs (in a broad sense, including physical hurdles, such as distance and available, to institutional ones such as tariffs and non-tariff barriers), denoted by $\kappa_t^{nj,ij}$, are of the standard "iceberg" type; for nontradable sectors, we assume $\kappa_t^{nj,ij} = \infty$.

Local Sectoral Aggregate Goods

In each country, all varieties of a given sector – acquired from the lowest cost supplier – are aggregated in a "composite" sectoral good Q_t^{nj}, which is used locally both for final consumption and for inputs in the production of all sectors. As shown in Appendix B.1, the local sectoral aggregator depends on the joint distribution of the vector z^j of a variety's productivities across different origins.

Local aggregator firms also operate in perfect competition, and the solution to their problem, given the properties of the Fréchet distribution of variety productivities, implies that it is possible to obtain a gravity-like equation for the fraction of expenditure in country n and sector j which is spent on varieties produced in country i, $\pi_t^{nj,ij}$ – which, as one would expect, will depend positively on productivity (that is, the higher A_t^{ij}, *ceteris paribus*, more will be spent on goods made in i) and negatively on transport costs:

$$\pi_t^{nj,ij} = \frac{(x_t^{ij}\kappa_t^{nj,ij})^{-\theta^j}(A_t^{ij})^{\theta^j\gamma^{ij}}}{\sum_{m=1}^{N}(x_t^{mj}\kappa_t^{nj,mj})^{-\theta^j}(A_t^{mj})^{\theta^j\gamma^{mj}}} \tag{2-4}$$

where γ^{ij} is the share of value added in intermediate goods production in country i and sector j.

Market Clearing and Equilibrium

The model accounts for the possibility of trade deficits by assuming the existence, in each country, of an unit mass of structure owners, which cannot migrate, and are paid the market rate r_t^{ik}; the revenue of all structure owners is deposited in a global fund in exchange for a constant share ι^n (with $\sum_{n=1}^{N}\iota^n = 1$) of this portfolio, which they use to consume local aggregates according to the same aggregator employed for other consumption. Trade imbalances, therefore, stem from the differences between structures rental revenues and the shares received by structures owners in each country, and are defined as $\sum_{k=1}^{J} r_t^{nk}H^{nk} - \iota^n \sum_{i=1}^{N}\sum_{k=1}^{J} r_t^{ik}H^{ik}$.

As shown in Appendix B.1, the introduction of labor heterogeneity impacts the market clearing conditions for the goods and labor markets (which now are two, one for each type). The market for each of primary factors clears if the factor's total payments equals its share in total value added; so, we have the following clearing conditions for each labor market:

$$U_t^{nj} w_{t,u}^{nj} = \upsilon_t^{nj} \gamma^{nj} (1 - \xi^n) \sum_{i=1}^{N} \pi^{ij,nj} X_t^{ij}$$

for unskilled labor, and

$$S_t^{nj} w_{t,s}^{nj} = (1 - \upsilon_t^{nj}) \gamma^{nj} (1 - \xi^n) \sum_{i=1}^{N} \pi^{ij,nj} X_t^{ij}$$

for skilled labor; X_t^{nj} denotes total expenditures in sector j in country n.

As for the goods market, the existence of two labor types only alters the determination of final demand (which now accounts to the consumption of the two kinds of household), so that the clearing condition becomes:

$$X_t^{nj} = \sum_{k=1}^{J} \gamma^{nk,nj} \sum_{i=1}^{N} \pi^{ik,nk} X_t^{ik} + \alpha^j \left(\sum_{k=1}^{J} (w_{t,u}^{nk} U_t^{nk} + w_{t,s}^{nk} S_t^{nk}) + \iota^n \sum_{i=1}^{N} \sum_{k=1}^{J} r_t^{ik} H^{ik} \right)$$

As in CDP, equilibrium is defined in a step-wise fashion that accounts for the nature of the model – which embeds successive trade models in each period of a dynamic occupational choice structure –, so that we define separately the equilibrium of the static subproblems (taking as given the period's state of the dynamic problem) and that of the dynamic problem (which also requires that all static subproblems are solved at each period)[7].

Therefore, as detailed in Appendix B.1, finding the static subproblem's equilibria in each period consists in obtaining wages and allocations that solve the agents' problems and clear all markets in the trade model, taking as given the period's value of the state variables and the fundamentals of the economy, while obtaining the dynamic equilibrium involves also the paths of each labor's allocations that solves the households' intertemporal problem.

2.2.2
Dynamic Hat Algebra

Given the richness of the structural model detailed in the previous subsection, CDP built on the idea originally devised by Dekle et al. (2008)

[7]See CDP and references therein for proofs of the existence and uniqueness of the two types of equilibrium.

(henceforth DEK) of rewriting the model in terms of differences between baseline and counterfactual values, so that many of the fundamentals of the model cancel out and need not be estimated – which, in the case of the present model with N countries, J sectors and T periods could entail the estimation of $N \times J$ mobility costs, $N^2 \times J \times T$ bilateral transport costs, and $J \times T$ productivity parameters, for example.

The method is a generalization, suitable for a dynamic structure, of the technique introduced by DEK to solve for counterfactuals in a static trade model. With the purpose of analyzing trade and wage effects of eliminating current account imbalances among a set of countries, DEK show that expressing the model in terms of percent changes between baseline and counterfactual values (that is, $\hat{x} \equiv \frac{x'}{x}$, whare $x\prime$ is the counterfactual value of a variable x – hence the name by which the technique is known, "exact hat algebra", coined by Costinot and Rodríguez-Clare (2014)), it is possible to solve the model without information on the levels of variables such as productivities and transport costs, and calculate counterfactual changes in the variables of interest.

Inspired in DEK, therefore, the method devised by CDP (which the authors name "Dynamic Hat Algebra") applies the same idea – expressing the model variables in changes, and not levels, to eliminate from the equilibrium conditions variables that are unobservable or too dificult to estimate – in a dynamic framework. CDP show that, under certain hypotheses, it is possible to rewrite the model's equilibrium conditions in terms of *time differences* – that is, $\dot{x}_{t+1} \equiv \frac{x_{t+1}}{x_t}$ – in order to find the model's solution by conditioning in usually available data – on bilateral trade flows and labor transitions, for example – with no needing to obtain unavailable information on levels of variables such as productivity and trade costs. Moreover, we can rewrite the model in terms of *ratios of time changes* between baseline and counterfactual – that is, $\hat{x}_{t+1} \equiv \frac{\dot{x}\prime_{t+1}}{\dot{x}_{t+1}}$, where $\dot{x'}_{t+1} \equiv \frac{x'_{t+1}}{x'_t}$ are the time differences in counterfactual equilibrium – in order to obtain the sequences of counterfactual values of interest variables, given any postulated change in the time path of any set of the model fundamentals – again, without the need to know or estimate the levels of those fundamentals.

As seen in the last subsection, introducing labor heterogeneity doesn't change all the equilibrium conditions of the model; therefore, as detailed in Appendix B.1, the conditions that involve only aggregate labor are identical to their counterparts in the original homogenous labor framework of CDP. We therefore highlight here only the ones that are modified in relation to the original model.

For the dynamic problem, we simply duplicate each modified equilibrium condition, one for each labor type. For the static subproblem, we have one additional equilibrium condition (equation (2-3)); in terms of time changes it becomes:

$$\dot{w}^{nj}_{t+1} = \left[\upsilon^{nj}_t (\dot{w}^{nj}_{u,t+1})^{1-\sigma} + (1-\upsilon^{nj}_t)(\dot{w}^{nj}_{s,t+1})^{1-\sigma}\right]^{\frac{1}{\sigma-1}}$$

Where υ^{nj}_t gives the share of unskilled labor in total labor payments in sector j of country n. We also now have two modified labor market clearing conditions, one for each labor:

$$\dot{w}^{nk}_{u,t+1}\dot{U}^{nk}_{t+1} = \frac{\upsilon^{nj}_t \gamma^{nj}(1-\xi^n)}{w^{nk}_{u,t}U^{nk}_t}\sum_{i=1}^{N}\pi^{ik,nk}_{t+1}X^{ik}_{t+1}$$

and

$$\dot{w}^{nk}_{s,t+1}\dot{S}^{nk}_{t+1} = \frac{\upsilon^{nj}_t \gamma^{nj}(1-\xi^n)}{w^{nk}_{s,t}S^{nk}_t}\sum_{i=1}^{N}\pi^{ik,nk}_{t+1}X^{ik}_{t+1}$$

where ξ^n is the share of structures in value added (so that $(1-\xi^n)$ is the share of aggregate labor in value added).

Similarly, for obtaining the counterfactuals, equation (2-3) expressed in ratios of time differences becomes:

$$\hat{w}^{nj}_{t+1} = \left[\upsilon'^{nj}_t (\hat{w}^{nj}_{u,t+1})^{1-\sigma} + (1-\upsilon'^{nj}_t)(\hat{w}^{nj}_{s,t+1})^{1-\sigma}\right]^{\frac{1}{\sigma-1}}$$

and the labor market clearing conditions are:

$$\hat{w}^{nk}_{u,t+1}\hat{U}^{nk}_{t+1} = \frac{\upsilon'^{nj}_t \gamma^{nj}(1-\xi^n)}{w'^{nk}_{u,t}U'^{nk}_t \dot{w}^{nk}_{u,t+1}\dot{U}^{nk}_{t+1}}\sum_{i=1}^{N}\pi^{ik,nk}_{t+1}X^{ik}_{t+1}$$

and similarly (with $1-\upsilon'^{nj}_t$) for S.

Notice that in these new modified equilibrium conditions we need also the counterfactual share of unskilled labor, which is obtained by:

$$\upsilon'^{nj}_{t+1} = \left[1 + \frac{(1-\upsilon'^{nj}_t)}{\upsilon'^{nj}_t}\left(\frac{\dot{w}^{nj}_{u,t+1}}{\dot{w}^{nj}_{s,t+1}}\right)^{\sigma-1}\right]^{-1}$$

2.3 Data, Calibration and Counterfactuals

In order to apply the solution method described in the previous section, two main datasets are required. First, we need cross-sectional data for the base year – including the initial distribution of the workforce across sectors; the share of labor in value added $1-\xi^n$, the share of value added in gross output γ^{nj}, input-output coefficients $\gamma^{nj,nk}$, which are constant due to the Cobb-Douglas production function; final consumption shares α^j; and the global portfolio shares ι^n. Second, in order to match the baseline model to the actual evolution of the economy in the period of interest, we need time-series data on bilateral trade flows and labor transition matrices. In this paper, we implement the model considering 24 sectors (agriculture; mining; 12 manufacturing sectors[8]; and 10 nontradable services sectors[9]) and 38 countries[10]; given data constraints and our focus on Brazil, we assume that labor is immobile in the remaining countries[11]. The time span covers the period from 2000 (the base year) to 2010.

Data comes from two main sources: the World Input-Output Database (WIOD) Timmer et al. (2015), which provides information on production and trade, and the dataset RAIS (Relação Anual de Informações Sociais), an official linked employer-employee dataset which covers with detail the Brazilian formal labor market as a whole. From the 2000 edition of WIOD we are able to calculate the share of value added in gross output γ^{nj} and the input-output coefficients $\gamma^{nj,nk}$; the share of labor in value added $1 - \xi^n$ is available on the Socio-Economic Accounts annex of WIOD. Also from WIOD (which is available yearly and covers the period from 1995 to 2014, therefore including the time span of this paper) we can build the time series of bilateral trade.

From RAIS, we are able to calculate readily the sectoral distribution of labor in the base year. Also from RAIS – which identifies workers using a time-consistent identifier – we are able to build a panel of workers and observe the year-to-year transitions across sectors. As mentioned, however, RAIS covers only the formal sector, which leads to two practical implications. First, the informal sector is lumped with unemployment in sector 0; in other words, this means that the model covers only the formal labor market. Second, transitions to and from unemployment/informality are not readily available, and must be inferred: we assume that a worker is unemployed when he does not appear on RAIS in a given year, but is present on previous and future years

[8]The tradable sectors are: Agriculture, Forestry and Fishing; Mining; Food, Beverages and Tobacco; Textiles, Leather and Apparel; Wood, Paper and Printing; Petroleum and Coal; Chemical Products; Plastic and Rubber; Non-Metallic Minerals; Primary and Fabricated Metals; Machinery; Computer and Electronics; Transport Equipment; and Furniture and Manufactures n.e.s.

[9]The nontradable sectors are: Wholesale and Retail; Construction; Transport Services; Information Services; Finance and Insurance; Real Estate; Education; Health Services; Accomodation and Food; and Other Services n.e.s.

[10]Apart from Brazil, the countries are Australia, Austria, Belgium, Bulgaria, USA, Canada, China, Cyprus, Czech Republic, Germany, Denmark, Spain, Estonia, FInland, France, Great Britain, Greece, Hungary, Indonesia, India, Ireland, Italy, Japan, South Korea, Lithuania, Mexico, Netherlands, Poland, Portugal, Romania, Russia, Slovakia, Slovenia, Sweden, Turkey, Taiwan, and a constructed Rest of the World.

[11]Similarly, CDP assume that labor is mobile only in US states.

(that is, before the first time he appears on RAIS she is considered not yet active, and after the last appearance he is considered retired). This procedure mechanically underestimates unemployment/informality in the initial and final years of the panel; to alleviate this problem, we constructed the panel using all years available (1994 to 2016), but compute the transitions only for 2000-2010. Also to minimize noise, we consider only male workers of age 25-60 that work at least 30 weekly hours. Workers with jobs in more than one sector are mapped to sectors by considering first their longest spell, then the job with highest wage, and third the one with longest hours worked.

RAIS also provided the data for the estimation of the labor transition elasticity $1/\nu$, estimated separately for each labor type following the procedure detailed in CDP – who adapted the original method in ACM to logarithmic preferences –, which involves regressing labor transition flows on wage ratios and future migration flows (that contain information on the option value of switching sectors)[12]. The coefficient on the wage ratio is equal to β/ν; using our preferred specification, the estimated coefficient is 0.16, which – considering the discount factor $\beta = 0.99$ – implies a value of $\nu = 6.17$. Finally, the trade elasticities θ_j were obtained from Caliendo and Parro (2015).

2.3.1 Estimating the China Shock

Estimates of the China shocks – on exports and on imports – were obtained through a procedure similar to the one devised by CDP, with the first stage adapted in order to be consistent with the interpretation of the shocks in Chapter 1. That is, instead of using a set of "similar" countries as instrument to the effect of China on Brazilian imports and exports, we used the same procedure adopted in Chapter 1 to obtain estimates of the Chinese-led excess growth in sectoral imports and exports of all countries except Brazil; these estimates were then used as instruments for the growth in Brazilian trade with China that was due to the latter.

These "first-stage" estimates were then used as the basis for the calibration of the changes in Chinese productivity that drive the each shock – unlike CDP, we allow for productivity changes in all sectors, not only on tradables; this will be crucial to generating the export shock, as discussed below. To do so, we use the simulated baseline model, and the counterfactual model assuming that only Chinese productivities ($\hat{A}_t^{\text{China},j}$) change – that is, in the counterfactual the growth in Chinese productivity is *smaller* than in the baseline model,

[12]We follow ACM and CDP in using lagged values of transition flows and wages to account for endogeneity

in order to "cancel out" its effect on trade. We iterate this counterfactual model, changing the assumed $\{\hat{A}_t^{\text{China},j}\}_{j=1,t=2000}^{J,2010}$, until the difference between the baseline (that contains the effect of the shock) and the counterfactual (in which the shock didn't happen) values of the bilateral trade flow in question minimizes the sum of squared differences to the magnitudes obtained in the first stage. This procedure is done separately for each shock (export demand and import supply), yielding two sets of counterfactual changes in Chinese productivity which underlie the two counterfactual scenarios discussed in the next section.

2.4 Results

In this section we will analyze the results of the counterfactual exercises that simulate the effects of the two sides of the trade shock induced by the rise of China as a major player in global trade. First, in subsection 2.4.1, we focus on the effects of the China shock on the sectoral dynamics of employment. As previously noted, the simple CES aggregation form assumed for combining labor types implies that the sector-level employment response of skilled and unskilled labor both go in the same general direction – although usually in different magnitudes due to the fact that each sector uses each labor in a different intensity and all sectors "compete" for attracting labor. We then focus the discussion of the sectoral employment effects on the response of aggregate labor, and only describe the behavior of each labor type when they differ in a meaningful way.

Second, in subsection 2.4.2, we present the distributional effects of the shocks, that is, the effects on skill composition of the workforce in each sector, and on the sectoral wage ratio between skilled and unskilled labor.

2.4.1 Effects of the China Shock on Sectoral Aggregate Employment

Import Shock

We begin by analyzing the effects of the import supply shock – that is, the increased availability of imports that emerges from the increase in Chinese productivity in tradable sectors, which increases the probability that China is the lowest-cost supplier of a good, and therefore increases the country's share in its partners' (including Brazil) expenditures. The ultimate effects on each sector will be driven by the interplay between this direct effect but also of other general equilibrium effects magnified by the presence of input-output linkages, such as the enlarged availability of cheaper supplies for other sectors (including nontradable ones), or the increased indirect demand of other goods as inputs for the sectors whose demand increase due to the shock.

Figure 2.1: Effects of China Import Shock on Employment Shares

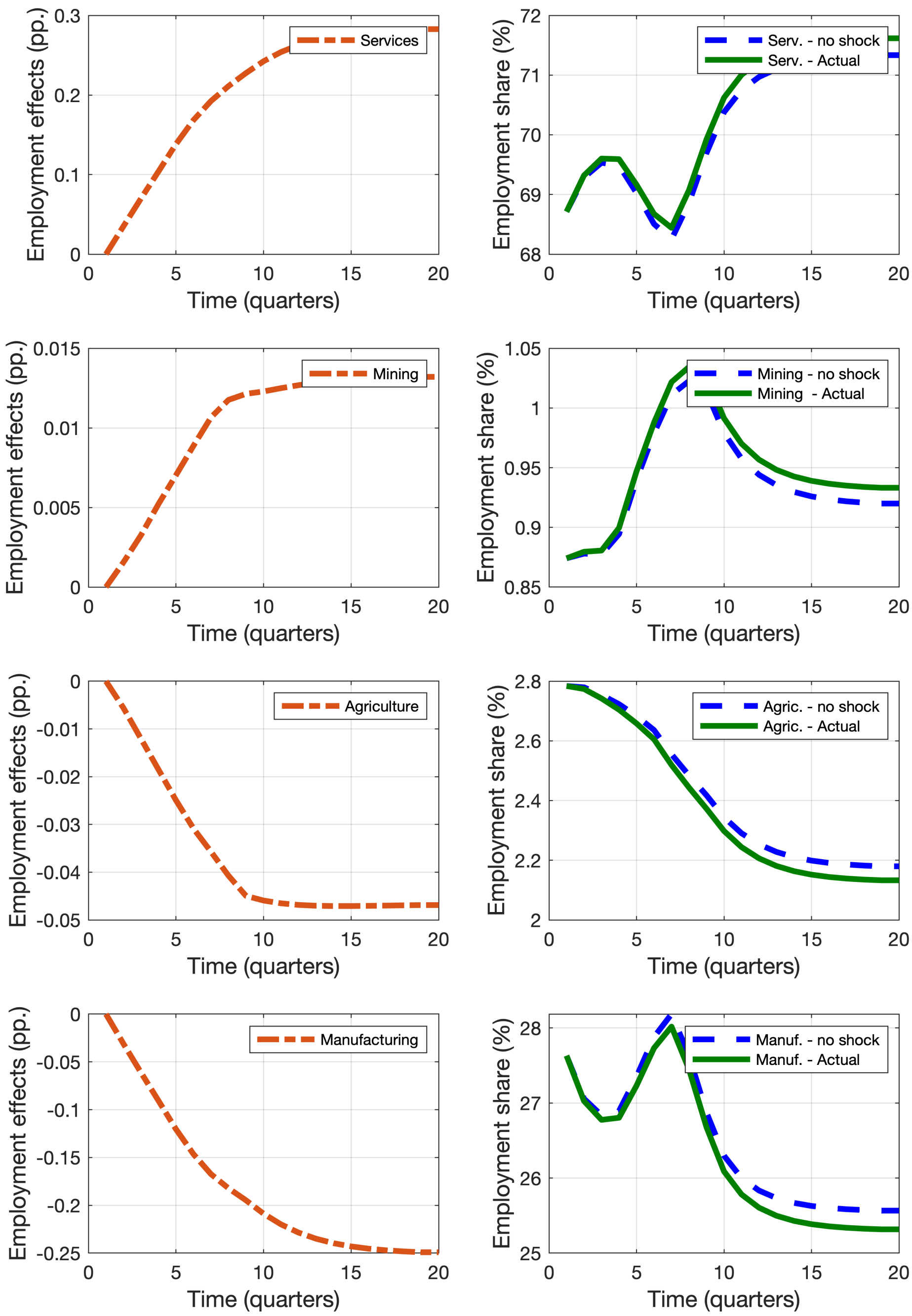


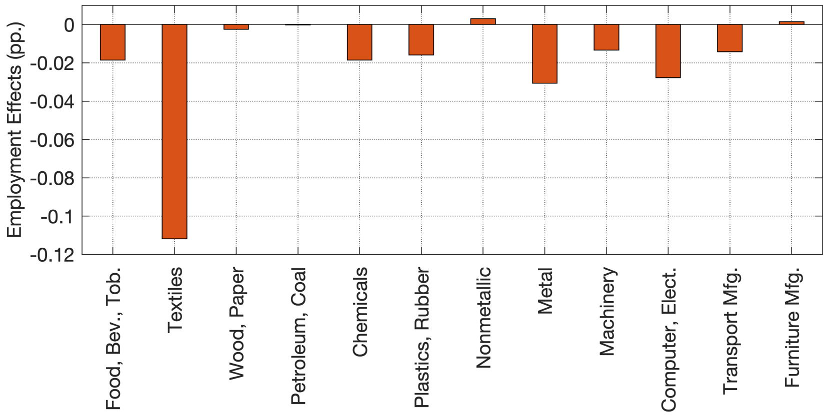
Figure 2.1 shows the dynamic effect of the import shock on the share of each aggregate sector's share in total employment. The left panels display the effects of the shock in each broad sector, which is given by the difference (in percentage points) in the employment shares of each sector with and without the shock – these are plotted in the right panels of figure 2.1, with the solid lines representing the actual situation (that is, where the shock happens as it actually did), and the dashed lines representing the counterfactual scenario where the shock did not happen. As displayed in the top-left panel, the increased availability of Chinese imported goods – which is mainly concentrated on manufactures – led to a decrease in the share of employment in manufacturing industries. The magnitude of the effect – which is about -0.21 percentage points after the shock plays out in 2010, and stabilizes in about -0.25 in the end of two decades – is equivalent to roughly 10% of the actual decrease in manufacturing employment observed between 2000 and 2010, displayed in top-right panel figure 2.1.

The burden of the adjustment is unequally distributed across sectors, as showed in the top panel of figure 2.2, which disaggregates the accumulated effect displayed in the top left panel of figure 2.1 across the 12 manufacturing industries. With a decrease of approximately 0.11 percentage points, the textiles, leather and apparel sector accounts for almost half of the reduction in total manufacturing employment (while accounting for only about 12% of total manufacturing employment in the initial period). Four sectors are hardly affected – two of which (nonmetallic minerals and furniture and other non-specified manufactures) are actually positively affected. The remaining seven sectors contribute moderately for the adjustment, each accounting for between 5% and 12% of the total effect on the manufacturing sector.

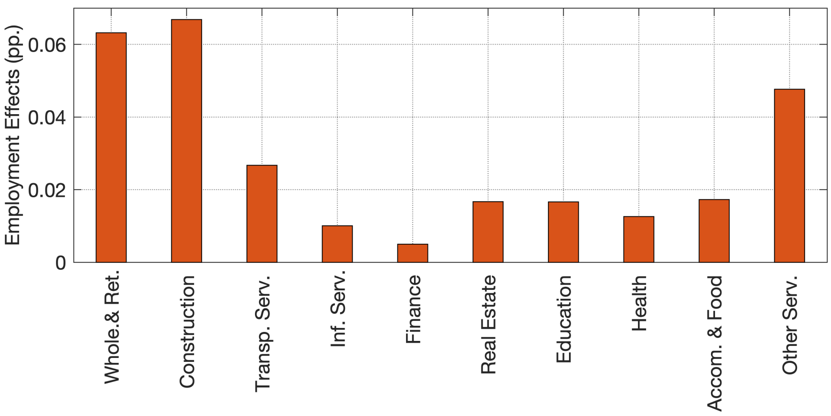
The other two tradables sectors are also affected, albeit in different directions. Employment in agriculture is negatively affected, with a relative magnitude similar to that obtained for manufactures: the decrease of about 0.05 percentage points is slightly below 10% of the actual decline in agricultural employment observed between 2000 and 2010. Employment on the mining sector, on the contrary, is increased by approximately 0.01 percentage points, which represents approximately 8% of the increase in mining employment in the period.

Figure 2.2: Contribution of Individual Sectors to Change in Employment

(a) Manufacturing Sectors



(b) Services Sectors



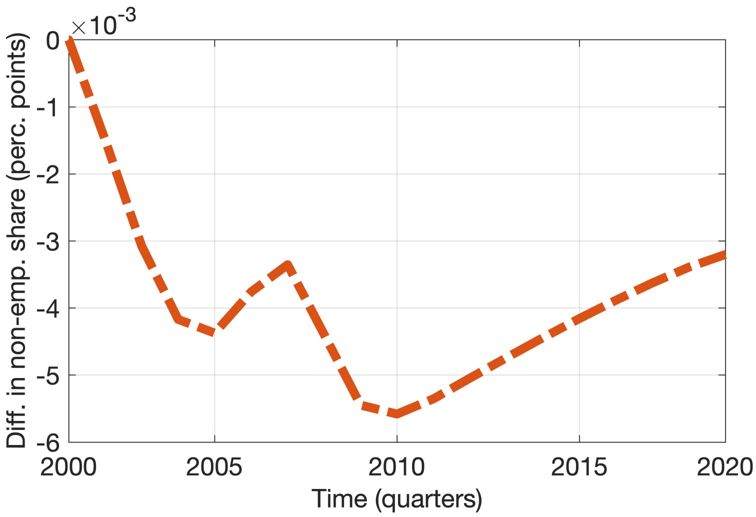
The nontradable sectors absorb the remaining of the employment driven out of the manufacturing and agricultural sectors, expanding as a response to the shock – this is consistent with the reduced-form evidence, discussed in Chapter 1, which points to a negative effect of the import competition shock on the share of tradables sectors in total employment.

The effect is also heterogeneous across services sectors, although less than with manufactures, as shown in the bottom panel of figure 2.2. All sectors expand, but three out of ten account for roughly 60% of the total increase in employment, led by the construction sector – which, while accounting for 12% of total nontradable employment, contributes with almost one quarter of the total effect.

The dynamics and magnitudes of the effects on the two labor types (in the Appendix) are broadly similar for mining, manufacturing and services. In agriculture, the trajectories are similar, but the fall is more intense for unskilled labor.

Finally, figure 2.3 shows that the loss of employment in tradables due to the increased competition with China is more than compensated by the expansion in mining and nontradable sectors which is made possible by the greater access to cheaper intermediate inputs; the ultimate effect is a decline (although very small) in "sector zero", which, as discussed, accounts for unemployment and informality (that is, those outside of RAIS). Although small, the direction of the effect is also consistent with the reduced-form evidence available in Chapter 1, which found that the import shock caused a decrease in informality as a share of total workforce (even though no effect was found on unemployment).

Figure 2.3: Effects of China Import Shock on Unemployment

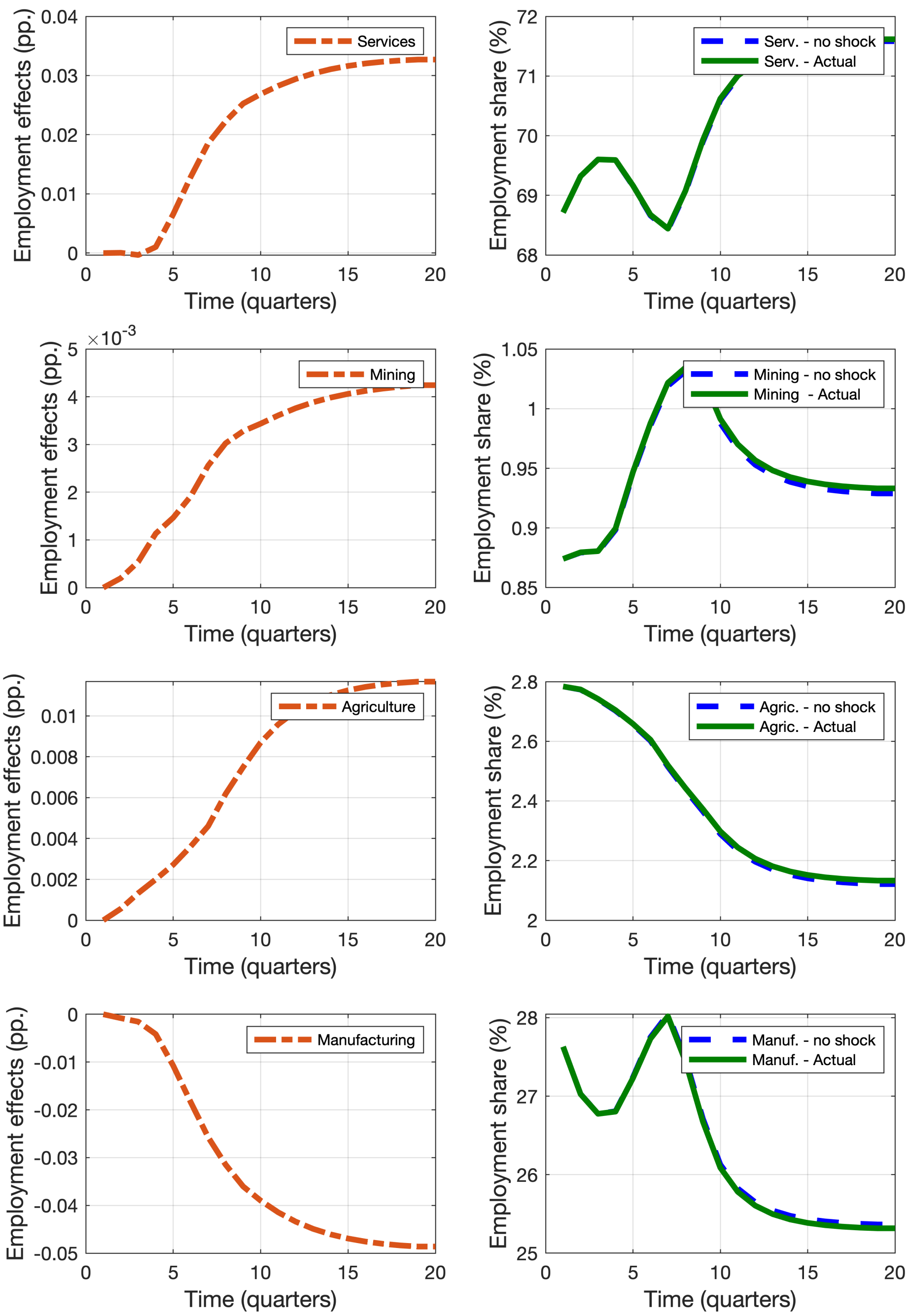


Export Shock

We now turn to the discussion of the export demand shock, that is, the increase in Brazilian exports to China driven by the productivity gains in the latter. The input-output linkages that characterize the structural model are key in driving this effect, which may derive both from the higher demand for intermediates in Chinese expanding sectors – including nontradable ones – and from the increased availability in inputs for production in Brazil.

It should be noted that, due to the Ricardian nature of the model, the effects of a Chinese productivity increase on another country's exports will probably be limited. The reason is twofold. First, since the increased demand for inputs in China – which is the main engine for the increase in Brazilian sales to that country – is likely to be taken advantage of by other countries as well, following the comparative advantage structure that underlies the pattern of global trade. Second, if the higher productivity in China takes place also in tradables, it is likely to result in this country becoming more competitive and expanding its sales at the expense of other partners, including Brazil, which may limit the increase in total Brazilian exports.

Figure 2.4: Effects of China Export Shock on Employment Shares



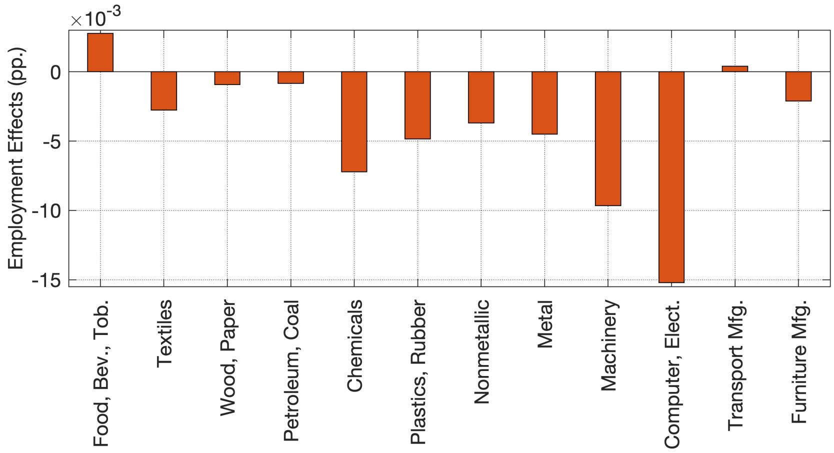
To see this latter mechanism, consider a simple example: contrast the effect of an increase in Chinese productivity in the construction sector – which is likely to lead to a higher demand of minerals and higher Brazilian exports both in this sector and overall – with an expansion of Chinese productivity in the steel sector – which may increase mining exports from Brazil, but simultaneously decrease Brazilian steel trades in third countries, with a possibly ambiguous net effect on Brazilian exports. For this reason, in the next subsection we discuss a third counterfactual exercise that may better emulate the effects of the commodities boom on Brazilian labor markets.

Figure 2.4 displays the effects on the employment shares of the four aggregated sectors. Unsurprisingly, the two commodities sectors expand their employment, reinforcing the idea that Chinese growth was a central engine of the so called "commodities boom" that induced the reprimarization of Brazilian export basket (the two sectors roughly doubled their share in baseline Brazilian exports between 2000 and 2010). The magnitudes are small, however, their absolute values accounting for around one fifth and one third of their import shock counterparts for agriculture and mining, respectively.

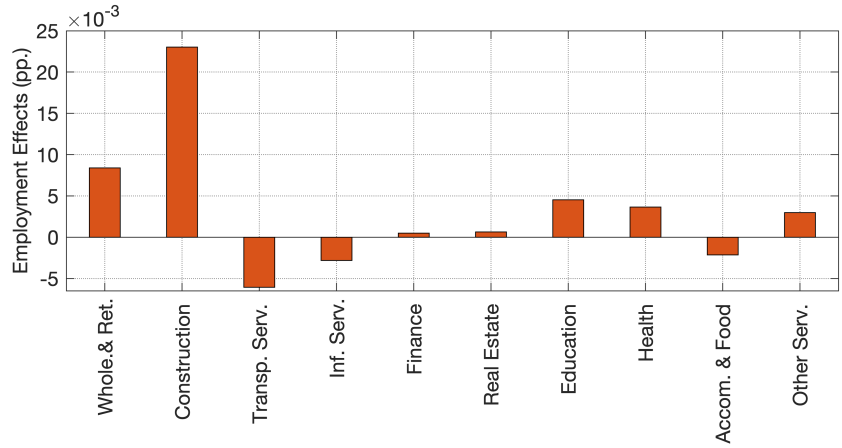
The effects of the export shock on manufacturing is less obvious, and illustrates the above caveat on the the possibility that the enhanced exports to China may be coupled with increased competition in third markets. On the aggregate, manufacturing employment decreases slightly; as shown in the top panel of figure 2.5, this effect is driven mainly by the two tradable sectors for which the Chinese productivity growth was the highest – machinery and computer/electronics, in which the Chinese global dominance was significant –, as well as the chemical sector in a smaller degree. However, the food and beverages sector – in which Brazil has a significant comparative advantage and is able to withstand competition in third markets –, employment actually grew as a response to the shock.

Figure 2.5: Contribution of Individual Sectors to Change in Employment

(a) Manufacturing Sectors

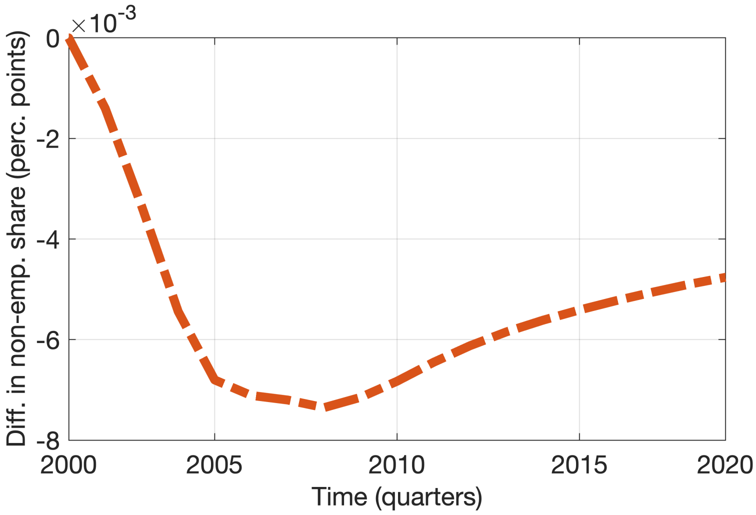


(b) Services Sectors



As with the import shock, the nontradable sectors absorbed the employment released from tradables as a net effect of the export shock. The magnitude is even smaller, slightly above one tenth of that of the import shock. The effect is mostly driven by the construction and wholesale & retail sectors, and unlike the previous counterfactual, not all sectors expand: transportation services, communications, and food and hospitality decrease their shares in employment, albeit by an almost insignificant amount.

Figure 2.6: Effects of China Export Shock on Unemployment

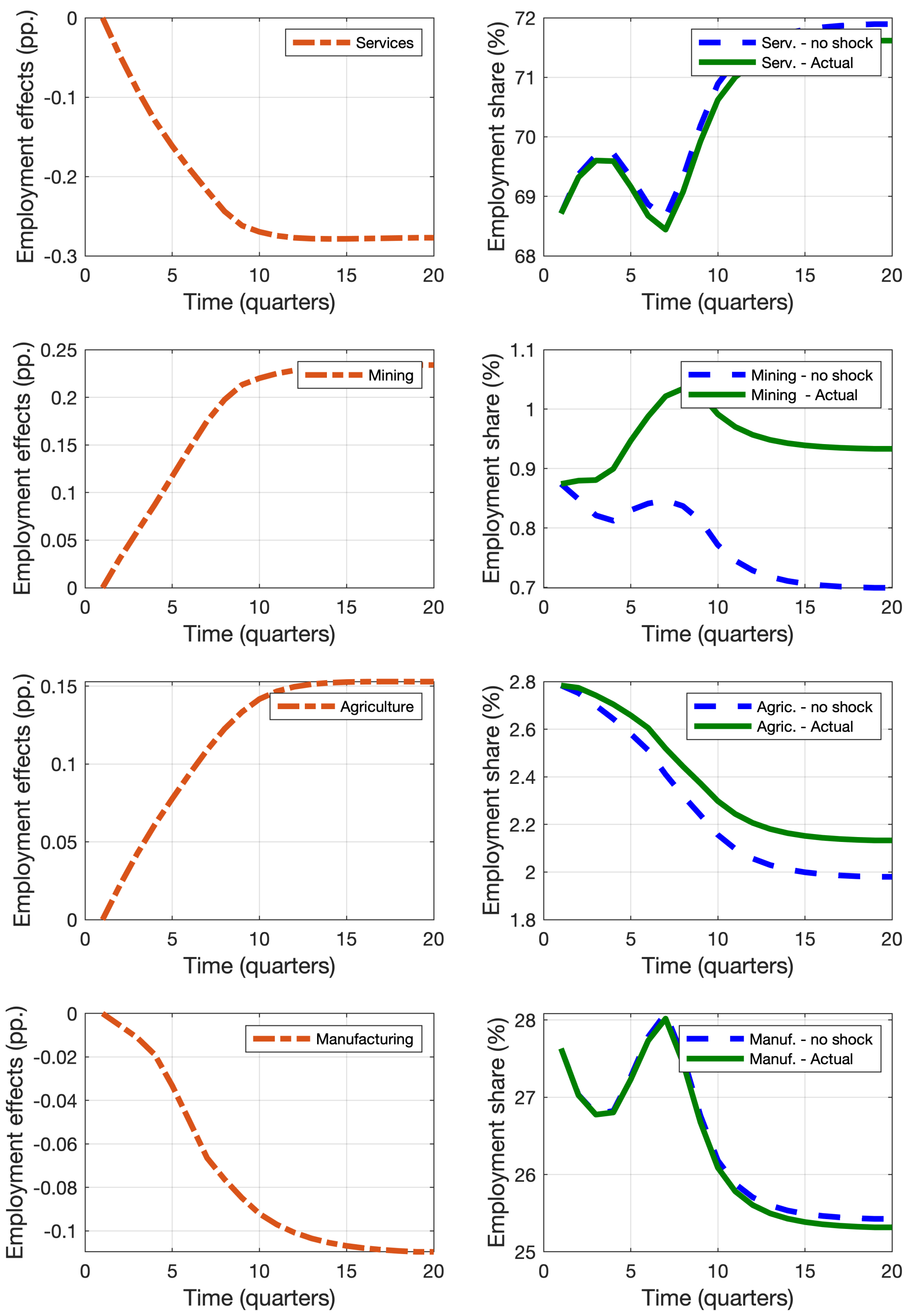


The effect of the export demand on unemployment is very similar to the previous counterfactual, with a small decrease in unemployment/informality – again, the direction of the effect is consistent with the reduced-form evidence in in Chapter 1, which points to the export shock contributing to expand formal employment from both informality and unemployment. However, as shown in the Appendix, the fall in unemployment/informality is driven by unskilled workers; for skilled ones it actually increases (although again with small magnitudes).

Alternative Shock

As discussed in the previous subsection, the Ricardian nature of the model that grounds the analysis in this paper implies that although an increase in Chinese productivity may generate an expansion in Brazilian exports to that country that matches the first stage estimate of the export side of the "China shock", it will also make Chinese goods more competitive – and more likely to substitute other sources (including Brazil) in third markets. As a consequence, the effect on Brazilian total exports, output – and ultimately employment – may be limited, understating the impact of the 2000's commodities-driven trade boom in the country's labor markets.

Figure 2.7: Effects of Commodities Productivity Growth on Employment Shares



Given this limitation, we perform an alternative counterfactual exercise in order to emulate this reprimarization of Brazilian export basket and analyze its effects on sectoral employment. In this exercise, the shock takes place in Brazilian productivity in the two commodities sectors – agriculture and mining –, and the target moment is the share of these two sectors in Brazilian total exports[13], which is assumed to remain constant in 2000 levels in the counterfactual. That is, in the counterfactual scenario all fundamentals evolve exactly as in the baseline economy, except for Brazil's productivity in these two sectors ($\{\hat{A}_t^{\mathrm{BR},j}\}_{j=1,t=2000}^{2,2010}$), which decline in such a way that the shares of agriculture and mining in Brazilian 2010 exports are the same as in 2000. Even though this exercise does not exactly represent a "trade shock" *per se*, it simulates a resource redistribution that would take place in the case of a trade shock that could drive a similar effect on total Brazilian exports, and helps put the magnitudes of the previous exercises in perspective.

As figure 2.7 shows, the effects on employment on commodities sectors are positive and much larger in magnitude than in the previous counterfactuals. The 0.15 percentage point increase in agricultural employment is equivalent to almost one third of the fall actually observed in the period. In the mining sector, the effect is even larger: in the counterfactual, employment in mining decreases instead of growing as it actually did.

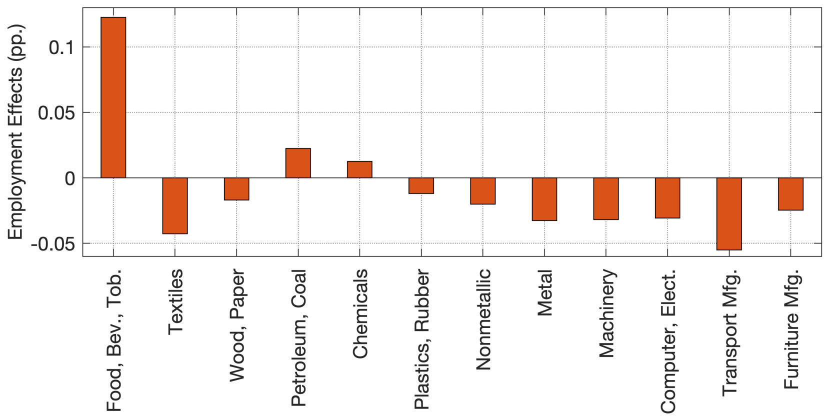
The share of the manufacturing sector as a whole in total employment decreases, as does the nontradables sector. However, while the decline in the latter is spread across all the sectors that make it up – especially in construction –, not all manufacturing industries see their employment decline. In fact, the food and beverages sector, which clearly benefits from the increased availability of agricultural inputs, expands in a magnitude that is larger than the sum of the aggregate decline.

Finally, as figure 2.9 shows, the shock also leads to a decline in unemployment/informality which is much larger than in the other counterfactuals – albeit accounting for only around 3% of the baseline expansion in formal employment between 2000 and 2010. Once again, even though the magnitude isn't large, the effect on employment is in the same direction pointed by the reduced-form evidence for the export shock.

[13] A similar exercise that targets the *levels* of the exports of these two sectors delivers qualitatively similar – if more intense in magnitude – results.

Figure 2.8: Contribution of Individual Sectors to Change in Employment

(a) Manufacturing Sectors



(b) Services Sectors

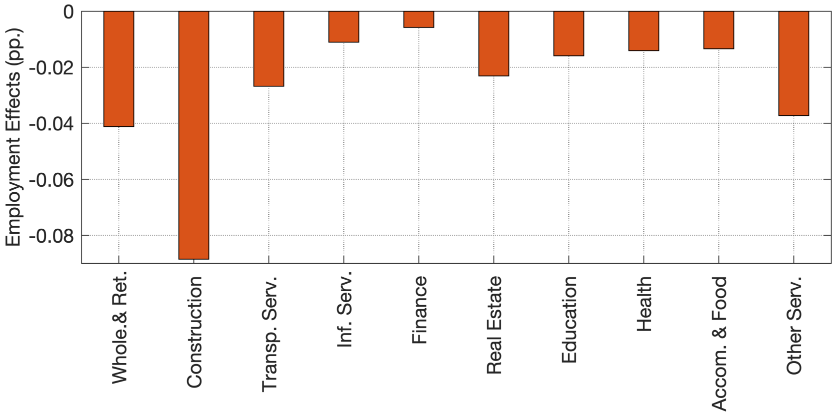
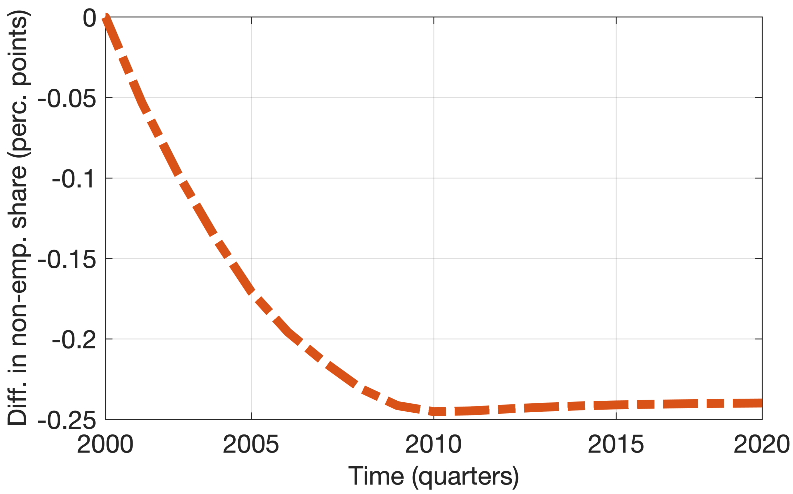


Figure 2.9: Effects of Commodities Productivity Growth on Unemployment

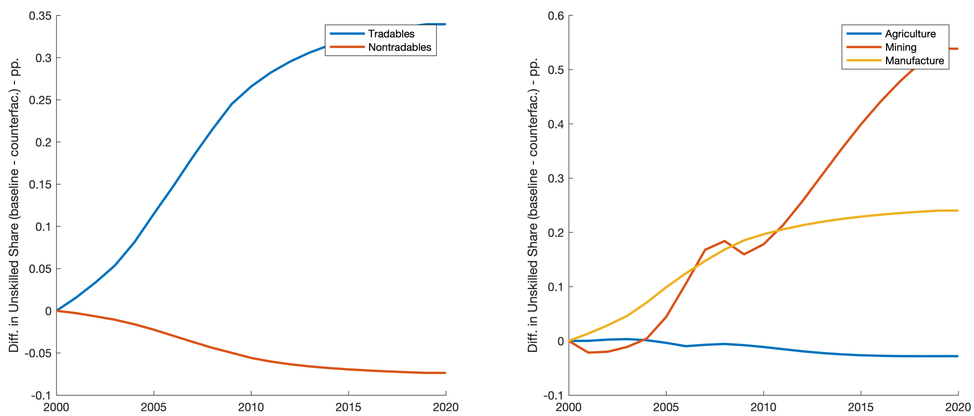


2.4.2
Distributional Effects of the China Shock

Import Shock

We now focus on the distributional effects of the import shock, that is, on its effects on the skill composition of the workforce in each sector and on the sectoral wage ratio between skilled and unskilled labor. The left panel of figure 2.10 pictures the effect of the shock in the share of unskilled workers in total labor, measured as the difference between the baseline share and its counterpart in the counterfactual where the shock did not happen, for tradables and nontradables. One can notice that the shock has increased the share of unskilled workers in tradables sectors, and decreased this share in nontradables. The direction of the latter effect is consistent with reduced form evidence presented in Chapter 1 which points to a positive effect of the import shock on the share of skilled workers (and thus a reduction in the share of unskilled workers), although the evidence for the tradables sector was too imprecisely estimated to lead to a conclusion.

Figure 2.10: Effects of the Import Shock on Unskilled Labor Share

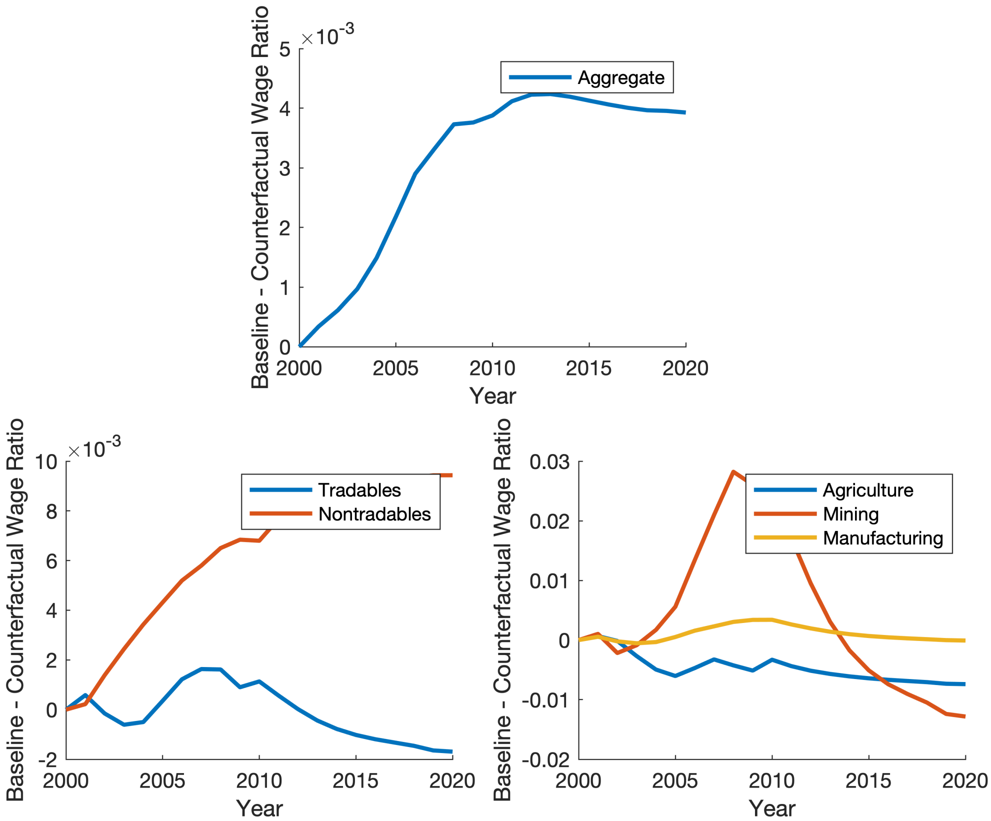


The right panel of figure 2.10 splits the effect on tradables across the three tradable aggregate sectors; it shows that the positive effect is driven by manufactures and mining, while the effect on agriculture is slightly negative. The magnitudes of the effects, however, are very small – as expected, given the reasons discussed above. All effects are equivalent to less than one percent of each sector's actual decline in unskilled labor between 2000 and 2010, except for the manufacturing sector which the effect is practically one percent of the actual decline.

To illustrate the effect of the shock on the wage ratio between skilled and unskilled labor, first we reconstruct the time series of baseline sectoral wages for each type of labor by applying the baseline time changes in real wages to the average sectoral wages obtained in RAIS; then we use the series of counterfactual ratios in time changes of real wages *vis-à-vis* the baseline economy to obtain the counterfactual wage series. Finally, the wage ratios are obtained for each sector by calculating the ratios between skilled and unskilled wages, and aggregate figures were obtained by weighting each sector by its share in total employment.

The top panel in figure 2.11 displays the effect of the import shock on the aggregate wage ratio of skilled and unskilled workers. The effect is positive, increasing in the duration of the shock and stabilizing after that. The magnitude is also very small: at its highest point (just after the shock has tapered off), the baseline ratio is only about 0.004 larger than the counterfactual; this difference is roughly 0.5% of the actual reduction in the wage ratio observed between 2000 and 2010.

Figure 2.11: Effects of the Import Shock on Wage Ratio



As one can see in the bottom-left panel of figure 2.11, this very modest increase in wage ratio is completely driven by the nontradables sector; in the tradables sector, the effect oscillates around zero while the shock is taking place, and converges to a even more slight reduction after Chinese productivity stabilizes. Once again, although the effects are small in magnitude, their direction is consistent with the aforementioned reduced-form evidence, which shows an increase in skilled labor wage premium in nontradables as a result of the China import shock, with no visible effect on the tradables sector.

Disaggregating further the tradables sector into agriculture, mining and manufactures, as in the bottom-right panel of figure 2.11, it is noticeable that each one contributes to the aggregate trend in a distinct manner. While the wage ratio for the manufacturing sector as a whole barely changes, agriculture experiences a very small but sustained decline, and the mining sector develops an interesting pattern, rising while the shock is active and reducing afterwards, eventually becoming negative. Moreover, albeit small, the effect on mining is an order of magnitude larger than the rest: at its height, the difference in wage ratio between baseline and counterfactual is approximately 0.03, or almost 4% of the actual increase in wage ratio observed in the period for this sector – which is the only of the tradables sectors which has experienced an actual increase in wage ratio.

Export Shock

We now turn to the analysis of the effects of the export supply shock. Unlike with the import shock, the export shock causes an increase in the unskilled labor share in both tradable and nontradable sectors, as shown in the left panel of figure 2.12; the magnitudes, however, are even smaller than in the previous shock. Also similar to the previous shock is the trajectory of the three tradables sectors, illustrated in the right panel of figure 2.12, although the rise is slightly larger for the mining sector.

The effects of the export shock on the wage ratio between skilled and unskilled workers, shown in figure 2.13, is even smaller than that of the import shock – this is a consequence of the already discussed fact that the nature of the model makes it difficult to a productivity increase in one country to generate a large increase in total exports of another country. Moreover, there is almost no increase – or decrease, for that matter – in the wage ratio for the nontradables sector, which drove the aggregate positive effect in the previous counterfactual. The trajectory of the wage ratio on the tradables sector as a whole is similar to that resulting of the import shock, as well as in the mining sector, while the roles of agriculture and manufacturing are reversed, with the former now increasing and the latter declining (both with very small magnitudes, however).

Figure 2.12: Effects of the Export Shock on Unskilled Labor Share

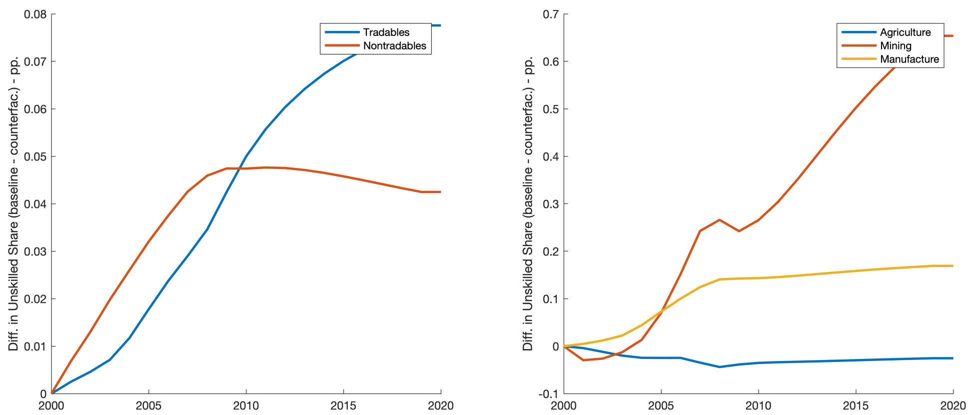
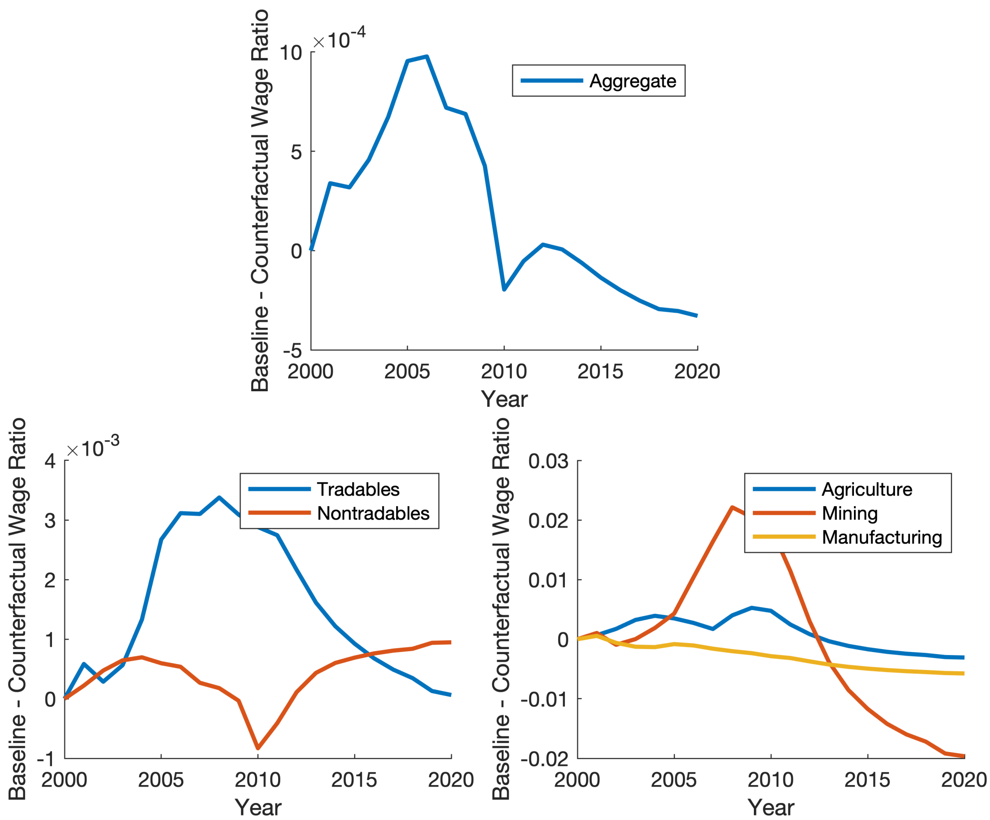


Figure 2.13: Effects of the Export Shock on Wage Ratio

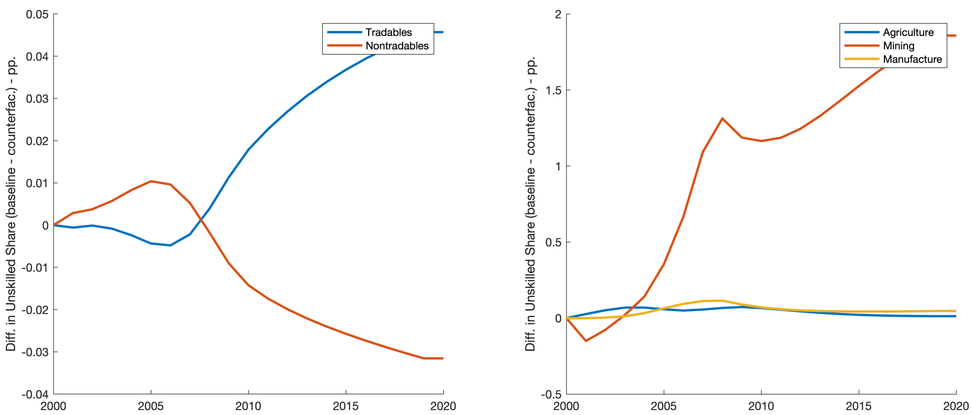


Alternative Shock

We end this subsection by presenting the results of the alternative shock on Brazilian productivity in commodities sectors, as described in the last subsection. Figure 2.14 displays the effects of this alternative shock on the unskilled labor share of employment. As the left-hand panel shows, the impact is almost symmetrical between tradables and nontradables: the former slightly falls at first and then reverses the trend, and conversely for the latter.

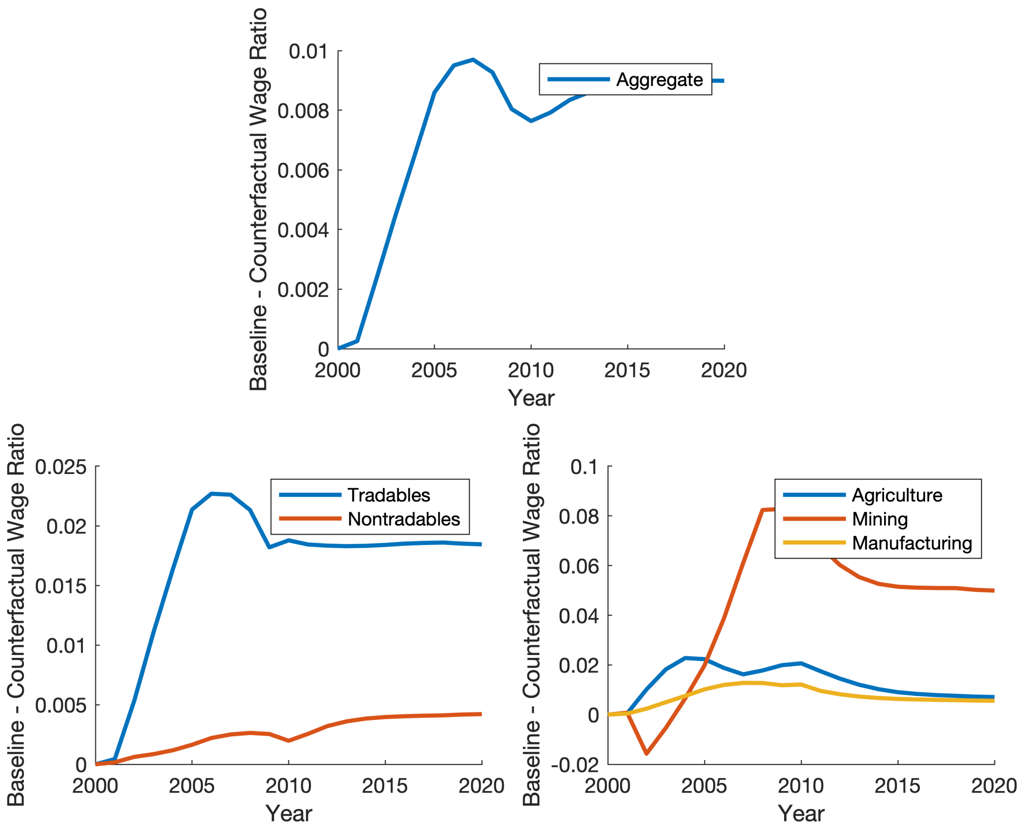
The right panel of figure 2.14, in turn, shows that, except for the first few years, the increase in use of unskilled labor happens not only in the commodities sectors, but also in the aggregate manufacturing sector. While the increase in agriculture and manufacturing are of similar magnitudes – even though the former is relatively more important, given the much smaller actual decline in its unskilled labor share –, in the mining sector the effect is almost 5% of the observed reduction between 2000 and 2010; albeit still relatively small, this magnitude is considerably larger if compared both to the other sectors and to the previous counterfactual scenarios.

Figure 2.14: Effects of the Alternative Shock on Unskilled Labor Share



Finally, the effects on the wage ratio between skilled and unskilled labor – displayed in figure 2.15 – is more than twice as large as in the previous counterfactuals, but still small: at its highest point, the magnitude of the increase is 1% of the actual decline in the wage ratio in the decade. As with the export shock, the increase is concentrated in the tradables sector – but unlike in that scenario, here the effects are long-lasting, and the magnitude is larger (around 1.5% of the observed decline). The wage ratio also increases in all three tradables sectors, and again mining is the most affected sector: while in agriculture and manufacturing the magnitudes are similar to that of the aggregate effect, in mining the peak effect is almost 10% of the actual increase in the wage ratio in this sector.

Figure 2.15: Effects of the Alternative Shock on Wage Ratio



Taken together, these results suggest that the model with heterogeneous labor implies modest distributional effects of the China shock in Brazil. As discussed, this was expected, not only due to the simple hypothesis on labor aggregation adopted in this paper, but also because of the small overall labor market effects that were the focus of the previous subsection. However, we should highlight that, albeit small, the results for the import side of the China shock are qualitatively similar to the reduced-form evidence presented in Chapter 1 in two central aspects: in nontradables, the shock increased the both the share of skilled labor and its wage premium *vis-à-vis* unskilled workers[14]. The effects of the export shock are even smaller; notice, however, that the reduced-form evidence found no visible effect of this shock on skill composition of the workforce, neither on skill premium for tradables or nontradables.

[14]Costa et al. (2016) also present evidence that the import side of the China shock may have increased the skilled labor premium, with no effects found for the export shock.

2.5 Concluding Remarks

We analyze the effects of the China shock to export demand and export supply on the dynamics of Brazilian labor market, using an extension of the multi-country, multi-sector general equilibrium framework developed by Caliendo et al. (2019) allow for heterogeneity in worker skill, so that we are able to analyze distributional effects driven by the relative demand for both types of labor. The model features a dynamic discrete choice problem of labor supply based in Artuç et al. (2010), in which families decide the sector they will seek employment taking into account wages, mobility costs, and an idiosyncratic preference component. In each period of the dynamic problem, wages are set through a static multi-sector Eaton-Kortum model developed by Caliendo and Parro (2015) which features intermediate consumption, input-output linkages between sectors, productivity differentials at the country and firm levels, and nontradable sectors. We also follow Caliendo et al. (2019) in rewriting the model in terms of time differences and ratios of time differences in order to simulate the model and perform counterfactual exercises without the need to estimate an infeasibly large set of parameters.

We calibrate the model using WIOD's global input-output data and a rich administrative dataset on Brazilian labor market, which allows for tracking worker transitions across sectors. The calibrated model is then used to perform counterfactual exercises simulating the push on Brazilian exports and imports led by the Chinese sectoral productivity growth.

Results suggest that the both sides of the China shock have contributed to the decline of manufacturing employment in Brazil in the first decade of this century, and that services sectors have absorbed most of the displaced workforce. Moreover, the import shock has also increased employment in mining and decreased in agriculture, and a reduction in unemployment and informality, while the export shock has driven an increase in both commodities sectors. However, overall the effects are modest, especially in the export shock.

An alternative counterfactual scenario was performed simulating the reprimarization of Brazilian export basket through shocks in local productivity of the commodities sectors. The results of this alternative counterfactual suggest that even in the case of export demand, the China shock is not enough to explain a significant part of the reshuffling of resources into commodities sectors.

Results also suggest that distributional effects of the China shock are small but consistent with reduced-form evidence obtained in Chapter 1, with the import shock reducing the share of unskilled workers in the nontradables sectors and increasing in the tradables sectors, and the export shock leading to an even smaller effect on the relative demand for labor types.

3
Lobbying Together for Protection: Industry Associations and Trade Policy in Brazil

3.1
Introduction

After a half-century long decline in government-imposed trade impediments, the last decade has witnessed a resurgence in protectionist measures across the world, first by an increasing number of countries resorting to non-tariff measures at the wake of the Great Recession, and more recently with even the United States imposing new and ad-hoc tariffs on its imports.

One suspect for this renewed departure from free trade is politics. In this context of turmoil, special interest groups are capable of organizing themselves in order to maintain or increase their protection from foreign competitors, as means to capture rents at the expense of the rest of society. The recent tariffs levied by the US on imports of steel and aluminum are a prominent example.

Brazil has been a forerunner in this upturn in protectionist industry-specific policies – the World Trade Organization's 2009 Trade Policy Review on the country (World Trade Organization (2009)), for example, points to an increase in average tariff protection since the previous report (in 2004), as well as the continuing active use of trade remedies to counter imports deemed as unfair. In fact, the liberalization process that extended from the late 1980s to the early 2000s was unable to eliminate the vestiges of special interests reflected in the structure of its trade policy, formed amidst an import-substitution effort of industrialization.

Another distinguishing characteristic of the Brazilian political economy is the fact that lobbying is illegal; therefore, producers must find alternative ways of advancing their special interests. One way of doing this is through joining efforts in trade associations or employer unions, which will intermediate the contact between firms and government authorities or institutions. This form of joint lobbying is particularly relevant for policies that are implemented at the product or industry level; this is usually the case of trade policy, which is hardly ever firm-specific: when a tariff or non-tariff measure is imposed on a certain good, it typically affects all producers of that good on an equal basis.

The goal of this paper is to investigate empirically the role of industry-level organizations in influencing trade policy formulation in order to attain sectoral interests. Specifically, we study whether industries with more political organization capable of obtaining more protection from foreign competitors than those who are less organized.

We begin by assembling a novel dataset on Brazil's trade associations in order to construct measures of political organization at industry level, based on the size of the associations that represent each sector. We then use variation in these measures to test whether sectors with more organization capacity have greater levels of trade protection.

The results show that, particularly in one type of non-tariff measure (non-automatic licensing), sectors with larger trade associations are more successful in obtaining protection from imports. Moreover, this effect is larger for industries that are subject to increased import penetration, suggesting that industries may be taking advantage of their lobbying capabilities to procure protection from foreign competition when this protection is especially needed. This relationship is robust to accounting for the role of factors that may be related to the size of an industry's trade union, such as the complexity of collective bargaining, or that could affect the level of protection, such as the share of intermediate products in a given industry. We also present suggestive evidence that the variation in trade association size may be inversely related to the evolution of an industry's productivity, which could indicate that industries turn to rent-seeking activities when their competitiveness is lacking.

We address the possible endogeneity of the import penetration measure, whose behavior could be capturing the effect of local phenomena such as industry-level shocks, by focusing on the so-called "China shock" – the rapid increase in Chinese competitiveness that led to an unprecedented increase in its participation in world trade in the turn of the XXIst century – as a natural experiment (as in Autor et al. (2013)). We follow Costa et al. (2016) and instrument bilateral Brazilian imports from China with a plausibly exogenous "counterfactual" trajectory of these flows obtained by multiplying baseline trade levels with a measure of the excess growth rate of China's exports in a given sector in comparison with the world average.

This paper contributes to a strand of literature on political economy of trade policy, strongly influenced by the seminal paper of Grossman and Helpman (1994), who modeled a game between sectors that could organize themselves to offer contributions to a government, which in turn would set up the protection structure taking into consideration these contribution schedules together with aggregate welfare.

A large part of the following literature in this area aimed empirically testing this model – from Goldberg and Maggi (1999) and Gawande and Bandyopadhyay (2000) to Imai et al. (2009) –, or at extending it to incorporate other features – one example is Bombardini (2008), which switches the focus from industries to firms, with larger firms being more likely to lobby and contribute, so that size distribution affects lobby participation shares and therefore the level of protection in a sector.

Unlike the majority of this literature, however – in which political organization is usually treated as a binary variable[1] –, this paper focuses on a non-binary measure of political organization capacity. That is, the question is not "whether an industry is organized or not" but rather "how organized is an industry", an idea similar to that of "lobbying effectiveness" in Saha (2019). This paper also complements this literature by focusing on how lobbying may affect *changes* in trade policy in response to an import shock, rather than their role in the determination of the overall protection level – as is the case in most of the PfS-derived literature.

More recently, a number of papers started to take advantage of new legislation imposing the disclosure of lobbying information in the United States to gather direct evidence on special interest politics; examples are de de Figueiredo and Silverman (2006), Bertrand et al. (2014), and – focusing on trade policy – Mishra (2010). Bombardini and Trebbi (2012) show that sectoral characteristics related to the degree of competitiveness will influence whether firms engage in lobbying activities alone or together in trade associations; an earlier version of this paper (Bombardini and Trebbi (2009)) shows that industries where firms lobby via trade associations obtain higher level of protection, which is in line with the evidence presented in this paper.

Because lobbying is not a regulated activity in many developing countries, including Brazil, the availability of this direct data on special interest activities are usually limited at best, which explain why most of the empirical literature on lobbying is circumscribed to developed countries (Bombardini and Trebbi (2020)). The contribution of this paper is, therefore, to propose a way of circumventing this limitation, by using alternative data that can help to shed light on special interest politics in developing countries. It is similar in purpose to other alternative measures of political connections, such as those that focus on name or surname coincidence between firm agents and political officials (Khwaja and Mian (2005); Lehne et al. (2018)).

[1]This is usually the case even when the binary variable is constructed from another one that is, in principle, continuous – as in one of the pioneering tests of the Grossman-Helpman model, Goldberg and Maggi (1999), which uses data on Political Action Committee contributions to create a dummy that is equal to one if a certain value threshold is reached.

The remainder of the paper is organized as follows. Section 2 briefly overviews institutional characteristics of trade policy formulation in Brazil. Section 3 presents the data and describes the empirical strategy, while section 4 report the main results and discuss their robustness. Section 5 presents our instrumental variables strategy for circumventing endogeneity in import penetration. Section 6 discusses the role of industry-level productivity, and section 7 concludes.

3.2 Institutional Environment

Despite being an original signatory of the 1947 General Agreement on Trade and Tariffs (GATT), Brazilian trade policy has been an instrument for active sectoral industrialization policies throughout most of the twentieth century. Two distinctive characteristics have emerged from this process. First, Brazil is an extremely closed country and, although significant progress has been made from the late 1980's until the mid 2000's in dismantling its protectionist structure, vestiges of the sectoral nature of its formation are yet visible, and there is still much leeway for implementing measures to limit imports. A second feature is that the authority in trade policy issues is concentrated in the hand of the executive branch, which is responsible for formulating and implementing policy changes; the legislative's role is basically limited to ratifying trade deals negotiated by the executive.

In analyzing the structure and determinants of Brazilian trade policy, one would be remiss not to take into account the central role of trade restrictive measures in the import substitution industrialization strategy, in which the stated goal was to dynamize growth through structural change, which in turn would be achieved by sheltering strategic manufacturing industries from foreign competition. Although the merits and success of this strategy was subject of extensive debates[2], it is undeniable that part of its heritage was the existence of a large and reasonably well difersified manufacturing sector, mostly characterized by low productivity and international competitiveness, but with strong political participation and close ties with policymakers. Another clear legacy was an almost autarkic economy, which in the late 1980s was protected by not only an average tariff of almost 60% but by an extremely bureaucratic system of multiple import regimes and prohibition lists (Baumann (1992)).

A period of trade liberalization lasted from 1987 to 1993, leading to a deep reformulation of the foreign trade structure, elimination of special regimes

[2]See Colistete (2010) for a review.

and of a large set of non-tariff barriers (notably of the prohibition lists), and a series of reductions in tariffs which slashed the average to 13% (Kume et al. (2003)). However, except for another brief tariff reduction in the onset of the "Plano Real" stabilization program (1994-1995), which took average tariffs down to near 11% (and was largely reversed more recently), that was the last concerted effort of trade liberalization that took place in Brazil (Abreu (2004)).

Despite these not so recent reforms and the limitations imposed by regional and multilateral negotiations – such as the WTO rules and the commitment to the South American Common Market (MERCOSUR) –, a number of measures are available for protecting domestic producers from foreign competitors. For example, although MERCOSUR is in practice a Customs Union, characterized by a Common External Tariff (TEC), each member is allowed to maintain a list of exceptions to the TEC, which gives the government latitude to modify tariffs (limited, however, by WTO bound rates). As for non-tariff measures, the menu is extensive, ranging from technical (Sanitary and Phytosanitary Measures and Technical Barriers to Trade) and contingent measures (antidumping, safeguards and countervailing duties) to quantity barriers such as quotas, prohibitions and non-automatic licensing, for example. Although ideally most non-tariff measures are not necessarily protectionist measures *per se*, and may pursue many valid policy objectives (such as protection from pests and diseases, for example), in practice they are often used as trade impediments.

The case of non-automatic licensing is exemplary: GATT provisions allows for countries to impose import licensing, defined as "administrative procedures requiring the submission of an application or other documentation (other than those required for customs purposes) to the relevant administrative body as a prior condition for importation of goods". In theory, non-automatic licensing should be used to manage other measures such as technical or quantitative restrictions, and should have no additional restrictive or distorting effects on imports. In reality, however, non-automatic licenses can be used to halt imports for up to 60 days without breaking WTO rules, and therefore can function as a short-term protectionist measure[3]. Grosso (2005) argues that this type of licensing may be used to control imports for economic reasons, and indeed has been traditionally used by developing countries especially to alleviate balance-of-payment difficulties. Unctad (2017) show that MERCOSUR countries still apply a large number of non-automatic licenses compared with other regions.

[3]In Appendix 1, we present and discuss some direct evidence on the effect of non-automatic licenses on trade.

In Brazil, this protectionist side of non-automatic licenses is aggravated by the fact that the institutional competence to impose these measures is a responsability of the Foreign Trade Secretariat (SECEX), part of the Ministry of the Economy. Therefore, special interest representatives (such as employer unions and trade associations) can solicit licensing for the range of goods they produce directly to SECEX staff, without having to gain access to higher-level authorities.

While SECEX is responsible for the implementation and daily operation of the trade policy system, the government body which centralizes most of the decision power on tariffs and other non-tariff measures is the Foreign Trade Chamber (CAMEX), an inter-ministerial council with an Executive Secretariat allocated in the Ministry of the Economy[4]. Although the original goals with the creation of CAMEX included streamlining the trade policy decision-making process and improving policy coordination among the different institutions involved in policymaking, the transfer of its Executive Secretariat to the former Ministry for Development, Industry and Foreign Trade (MDIC) has gradually led it into a more operational role, while simultaneously increasing its ties with the industrial sector (Fernandes (2013)). As stressed by Oliveira et al. (2019), this institutional feature – the subordination of trade policy operational and agenda-setting bodies to a ministry with close links to the manufacturing sector – "has given import-competing industrial sectors an edge in advancing their interests".

The authors also point to the fact that neither the aforementioned trade liberalization episodes nor the relative shrinkage of the industrial sector in Brazil's economy were capable of neutralizing the dominance of protectionist manufacturing interests in the political economy of the country's trade policy, and that a main pillar of this influence rests in the activity of sectoral organizations, such as trade unions and associations, which gravitate around a national confederation (the National Confederation of Industry, CNI) of state-level federations. Some of these associations, which have "close relationship with (and access to) government high-level officials", employ technical staffs dedicated to trade issues and usually represent the constituent firms before government agencies, taking advantage of the direct contact and "informal dialogue" maintained with the government.

3.3 Data and Empirical Strategy

[4]Until 2018, and for most of their existence, both CAMEX's Executive Secretariat and SECEX were under the Ministry for Development, Industry and Foreign Trade (MDIC).

3.3.1 Data Sources and Construction

In order to construct industry-level measures of political capacity, we have assembled a novel dataset of trade association characteristics. The list of trade associations was obtained in the website of the Federation of Industries of São Paulo (FIESP)[5], Brazil's largest and most industrialized state (accounting for almost one third of the country's manufacturing GDP). The characteristic used as a measure of trade association capacity (namely, its size measured as the number of employees as of December of each year[6]) was obtained from Relação Anual de Informações Sociais (RAIS), a yearly linked employer-employee database encompassing Brazil's formal labor market. Each trade association was mapped to the industry[7] (or industries) it represents through its name or, when the information was available, through the industries of the affiliated firms. Finally, to obtain the industry-level measures, we took the average size across all the unions that represent a given sector.

Initially, both tariffs and non-tariff barriers were used as measures of trade protection. Tariffs were obtained from the WTO's Tariff Analysis Online at the eight-digit level of the Harmonized System (the aggregation level in which tariffs are defined in Brazil), and averaged across all tariff lines in each industry. Data on non-tariff measures is from the Trade Analysis Information System (TRAINS), maintained by the United Nations Conference on Trade and Development (UNCTAD). The measure adopted is the Prevalence Index, given by the ratio of total measures to the number of (HS 6-digit) products in each industry; this is to take into account the fact that industries with more HS-6 products are likely to have a larger number of measures.

Trade data are from the BACI database, developed by Centre d'Etudes Prospectives et d'Informations Internationales (CEPII). The measure of import penetration used is the ratio of total imports to the value of industrial production, obtained from the Pesquisa Industrial Anual (Yearly Industrial Survey, PIA), conducted by the Brazilian Institute of Geography and Statistics (IBGE).

Industry characteristics used as controls were obtained from RAIS and

[5]Future work will also include the associations from other Brazilian States.

[6]Alternatively, we also used trade associations' total payroll instead of employment, obtaining qualitatively similar – albeit less precisely estimated – results, which are presented in the Appendix.

[7]The definition of industry used is the Classificação Nacional de Atividades Econômicas (CNAE), a classification based on the UN Statistics Division's International Standard Industrial Classification of All Economic Activities (ISIC). The level of aggregation adopted was 3 digits, which amounts to a total of 223 industries, of which 119 are considered tradable sectors.

from PIA/IBGE. Employees' unionization rate, given by the ratio of unionized to total employees in each sector, are from the Pesquisa Nacional por Amostra de Domicílios (PNAD), also conducted by IBGE.

Table 3.1: Summary Statistics

	Observations	Mean	S.D.	Min.	Max.
Trade Association Employment (log)	1,372	1.41	1.08	0	3.81
Average Tariff	1,372	14.37	6.40	0	35
Prevalence Index (all NTMs)	1,372	6.23	6.99	0	35.36
Prevalence Index (Non-Automatic Licensing)	1,372	0.55	0.85	0	3.81
Import Penetration (log)	1,372	-5.64	-2.54	14.19	1.97
Industry's Number of Firms (log)	1,372	5.71	1.09	1.39	8.46
Industry's Number of Workers (log)	1,372	10.43	1.05	4.74	12.87
Industry's Total Wages (log)	1,372	13.48	1.18	6.89	16.33
Industry's Employee Unionization Rate	1,358	0.26	0.11	0	1
Share of Non-Final Goods	1,372	0.79	0.30	0	1

Notes: Descriptive statistics for the variables used in this paper. Trade association employment data from RAIS. Tariff data from WTO (Tariff Analysis Online); simple average of all products in each industry. Non-Tariff Measures data from TRAINS/UNCTAD. Industry's Number of Firms, Workers and Wages from PIA/IBGE. Employee Unionization data from PNAD/IBGE.

3.3.2 Empirical Strategy

An obvious difficulty in evaluating the effect of political organization on import protection is the fact that trade association capacity is not randomly assigned to industries. In fact, there are probably a host of industry characteristics that affect both the sectors' political capacity and trade policy outcomes. The ideal experiment in this context – distribute political connections randomly across industries and observe how it affects the structure of protection – is evidently not feasible.

Models of endogenous lobby formation such as Mitra (1999), for example, suggest that a number of factors may influence a sector's organization, from an abstract "organizational ability" to more concrete characteristics such as the industry's size and geographical concentration – or, simply, the fact that some sectors may have formed an association for other (non-trade related) reasons – sharing technical know-how, for instance – and thus may already have an "installed" organizational capacity. In order to minimize the impact of these confounding factors, we use industry fixed-effects to eliminate constant unobserved variables that might introduce endogeneity. Moreover, we control for a set of industry characteristics, taking into account the fact that larger industries are likely to have, ceteris paribus, larger trade association. The baseline specification, therefore, is:

$$Y_{it} = \alpha_i + \alpha_t + \beta_1 TradeAssocCapacity_{it} + \Gamma X_{it} + \epsilon_{it} \tag{3-1}$$

where Y_{it} are the measures of protection, and $TradeAssocCapacity_{it}$ the measures of industry political organization; α_i and α_t are industry and year fixed effects; and X_{it} is a vector of industry characteristics including the number of firms, the number of employees, and total wages in a sector. The coefficient of interest is β_1, and the expected positive coefficient would indicate that larger trade association capacity is associated with higher import protection. It should be clear that the focus here is on *changes* in import protection, rather than the overall *level* of protection – unlike, for example, the bulk of the literature following the PfS approach, which considers the endogenous determination of the latter.

Since there may be multiple reasons for industries to have more powerful trade associations, we also control for import penetration following the so called "China shock" – the rise of China as a major trading power in the turn of the XXIst century – as a measure of the need for protection. The underlying reasoning for this strategy is that if a given sector experiences a relatively large increase in its import penetration due to the surge in Chinese exports, it will have an incentive to use its political capacity more intensively in order to demand more protection to counter this heightened foreign competition. This idea is reminiscent of the "surge protection" model (Imai et al. (2009)), in which a sudden increase in imports above a threshold level will trigger demand for protection, which is more likely to be transformed in actual protection measures if a sector is politically organized. This second specification is thus given by:

$$\begin{gathered} Y_{it} = \alpha_i + \alpha_t + \beta_1 TradeAssocCapacity_{it} + \beta_2 ImportPenetration_{it} + \\ \beta_3 UnionCapacity_{it} * ImportPenetration_{it} + \Gamma' X_{it} + \epsilon_{it} \end{gathered} \tag{3-2}$$

where $ImportPenetration_{it}$ is the penetration of imports from China, that is, the ratio of imports from China to the value of industrial production. The coefficient on the interaction of $TradeAssocCapacity_{it}$ and $ImportPenetration_{it}$, therefore, gives the compounded effect of import penetration on the relationship between trade association capacity and the protection measure. Its expected sign is also positive, implying that larger increases in import penetration would augment the effect of political capacity on import protection. It should be noted that this mechanism could be interpreted in terms of a specific factors model – in which the owners of capital that is specific to a certain sector have an incentive to prevent competition from foreign producers in the same sector –, as opposed to a Hecksher-Ohlin model in which capital owners would favour protection against capital-intensive imports, for example; that is, the dispute over trade policy will occur along sectoral divisions, rather than across factors of production.

3.4 Results

3.4.1 Trade Associations and Import Protection

The main goal in our empirical exercise is to assess whether industries with stronger trade associations – where "stronger" means more capable to perform lobby activities, proxied by the number of employees of the trade associations[8] – are able to obtain higher levels of protection from foreign competition. Estimates for the baseline specification (equation 3-1) are reported in Table 3.2. All specifications include industry and year fixed effects; those in even-numbered columns also control for industry-level characteristics obtained from RAIS data (number of firms, total employment and average wages) and from PIA (number of plants, total employment, and average wages). The time frame for all empirical exercises spans from 1999 to 2014.[9]

Estimated coefficients for the effect of trade association employment in average tariffs (columns 1 and 2) and the prevalence index of all non-tariff measures (columns 3 and 4) are statistically indistinguishable from zero, indicating that trade association size is not related with these broader measures of protection from imports. When one focuses on non-automatic licensing, columns 5 and 6 – the estimated effect is positive and statistically significant even when controlling for industry-level characteristic, suggesting that increases in the strength of trade unions are associated with higher prevalence of this type of measure.

Given that there may be a host of reasons for industries to have larger trade associations, we control for variation in import penetration following the China shock as a measure of the need for protection, based on the rationale

[8]Using trade associations' payroll instead of employment yield qualitatively similar – although less precisely estimated – results, which are presented in the Appendix.

[9]This corresponds to four complete federal election cycles: 2002, 2006, 2010 and 2014.

that a relatively large increase an industry's import penetration due to the surge in Chinese exports would encourage it to use its political capacity more intensively and bid for higher protection from foreign competition. The estimates for the resulting specification (equation 3-2) are displayed in table 3.3, again controlling for industry-level characteristics in the even-numbered columns.

Table 3.2: Trade Association Employment and Protection Measures

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Average Tariff		NTMs (Prevalence Index)		Non-Automatic Licensing (Prevalence Index)	
	OLS	OLS	OLS	OLS	OLS	OLS
Trade Association Employment (log)	0.658 (0.599)	0.692 (0.563)	-0.117 (1.041)	-0.142 (1.037)	0.098 (0.040)**	0.096 (0.038)**
Industry Controls	No	Yes	No	Yes	No	Yes
Industry and year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,372	1,323	1,372	1,323	1,372	1,323
R-squared	0.228	0.268	0.544	0.557	0.273	0.301
Number of cnae	88	88	88	88	88	88

Notes: This table reports the effect of trade association employment on protection measures at industry (3-digit CNAE) level. All columns report the results of OLS panel regressions where the dependent variable is the protection measure for a given industry in a given year, and the variable of interest is the log of the number of workers employed by all trade associations that represent an industry in a year. Average tariff is the simple average of the tariffs on all goods (6-digit level of the Harmonized System) in an industry. NTMs refer to all measures included in the UNCTADs classification of non-tariff measures. The prevalence index is the total number of measures imposed on all goods in an industry, divided by the total number of goods in that industry. Industry controls include the number of firms, the number of employees, and total wages in a sector. All specifications include industry and year fixed-effects. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Once again, the estimates for the effect of trade association employment on average tariffs and on the prevalence of all non-tariff measures are not statistically significant. As for the effect on non-automatic licensing, the coefficient is positive and statistically significant, and point estimates are more than double compared to the ones obtained when import penetration is not accounted for. The implied relative magnitude is such that, considering the more demanding specification (column 6), increasing the trade association's employment by one standard deviation from the mean would result in an increase of approximately 15% of a standard deviation in the prevalence of non-automatic licenses.

The coefficients on the interaction of trade association size with import penetration suggest that when the need for protection is more pressing (that is, when the increase in import penetration is higher), the effect of trade association capacity on licensing is compounded. Considering again the specification with industry-level controls (column 6), increasing import penetration from percentile 25 to percentile 75 more than doubles the magnitude of the effect of trade association employment on the prevalence of non-automatic licensing.

Table 3.3: Trade Association Employment, Import Penetration and Protection Measures

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Average Tariff		NTMs (Prevalence Index)		Non-Automatic Licensing (Prevalence Index)	
	OLS	OLS	OLS	OLS	OLS	OLS
Trade Association	0.813	0.896	1.119	1.289	0.233	0.222
Employment (log)	(0.825)	(0.772)	(1.274)	(1.228)	(0.069)***	(0.069)***
Import Penetration (log)	-0.015	-0.038	-0.386	-0.562	-0.041	-0.042
	(0.136)	(0.111)	(0.204)*	(0.225)**	(0.010)***	(0.011)***
Trade Assoc. Employment	0.026	0.035	0.225	0.260	0.025	0.022
X Import Penetration	(0.071)	(0.069)	(0.098)**	(0.105)**	(0.006)***	(0.006)***
Industry Controls	No	Yes	No	Yes	No	Yes
Industry and year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,372	1,323	1,372	1,323	1,372	1,323
R-squared	0.229	0.268	0.551	0.566	0.341	0.355
Number of cnae	88	88	88	88	88	88

Notes: This table reports the effect of trade association employment and import penetration on protection measures at industry (3-digit CNAE) level. All columns report the results of OLS panel regressions where the dependent variable is the protection measure for a given industry in a given year, and the variables of interests are the log of the number of workers employed by all trade associations that represent an industry in a year, and the interaction of the latter with log import penetration measured as the ratio of total imports to the value of industrial production. Average tariff is the simple average of the tariffs on all goods (6-digit level of the Harmonized System) in an industry. NTMs refer to all measures included in the UNCTADs classification of non-tariff measures. The prevalence index is the total number of measures imposed on all goods in an industry, divided by the total number of goods in that industry. Industry controls include the number of firms, the number of employees, and total wages in a sector. All specifications include industry and year fixed-effects. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.4.2 Robustness

The previous results showed that, in line with our main hypothesis, industries with larger trade associations show higher prevalence of one type of non-tariff measure – non-automatic licensing – that may provide protection from foreign competition. Moreover, the results also suggest that, consistent with our rationale, this increase in protection is larger when protection is more needed – that is, when industries are faced with a surge in imports. In this subsection we examine the possibility that other confounding factors may be influencing our results.

Our first focus is on employee unions. One reason that could lead an industry to opt for a larger trade association could be the complexity of the collective bargaining among employers and employees, which could lead to a correlation between the size of employee unions and that of employer unions (that is, trade associations). On the other hand, the existence of short-term specificities in labor across sectors, introducing the possibility of adjustment costs to workers whose industry of employment is negatively affected by trade shocks, suggests that labor may also be interested in protection from foreign competitors.

This idea is far from new: Baldwin (1984), for example, developed a simple trade model where not only capital but also labor is quasi-sector-specific in the short run, due to the existence of industry-specific skills; a sector change would then reduce the marginal productivity of labor (since a skilled worker from one sector would become a unskilled worker in a different sector), decreasing wages – thus giving labor unions an incentive to lobby for protection alongside their employers. More recently, Matschke and Sherlund (2006) introduce collective bargaining, differences in inter industry labor mobility, and trade union lobbying into a model similar to Grossman-Helpman's protection-for-sale framework, and show that these labor market variables are relevant to the determination of equilibrium in the lobbying game; in particular, they show that since workers receive part of the protection rents, equilibrium protection will be lower than predicted in the Grossman-Helpman model if workers do not accompany their employers in lobbying for trade policy.

Therefore, one immediate question one might ask about the influence of special interests in trade policy formulation concerns the role of employee (alongside with employer) unions. The regressions whose estimates are reported in the first two columns of Table 3.4 address this issue, including a variable on employee union capacity (the industry's employee unionization rate[10]) in the previously mentioned specifications (equations 3-1 and 3-2).

As the estimates suggest, however, the role of employee unions seems limited: coefficients are usually positive, but imprecisely estimated, and statistically significant only at the 10% level. Moreover, the inclusion of the employee

[10]Results using the number of unionized employees are similar, and are presented in the appendix. The ideal procedure here would be to include the same variables used for employer unions – number of employees and payroll. However, the high fragmentation of labor representation in Brazil (with around 12000 employee unions) precludes the construction of a similar dataset to that built for employer unions in this paper.

unionization rate variable have almost no effect on the other variables of interest: both the coefficients and standard errors of trade association employment remain practically unchanged, as well as the interactions with import penetration.

Table 3.4: Robustness

Variables	(1)	(2)	(3)	(4)
	Non-Automatic Licensing (Prevalence Index)			
	OLS	OLS	OLS	OLS
Trade Assoc. Employment (log)	0.099	0.223	0.096	0.221
	(0.038)**	(0.068)***	(0.038)**	(0.069)***
Employee Unionization Rate	0.146	0.140		
	(0.080)*	(0.083)*		
Share of Nonfinal Goods			-0.134	-0.067
			(0.097)	(0.112)
Import Penetration (log)		-0.043		-0.042
		(0.011)***		(0.011)***
Trade Assoc. Employment X Import Penetration		0.023		0.022
		(0.006)***		(0.006)***
Industry Controls	Yes	Yes	Yes	Yes
Industry and year FE	Yes	Yes	Yes	Yes
Observations	1,309	1,309	1,323	1,323
R-squared	0.305	0.360	0.302	0.355
Number of cnae	88	88	88	88

Notes: This table reports the effect of trade association employment and import penetration on protection measures at industry (3-digit CNAE) level. All columns report the results of OLS panel regressions where the dependent variable is the protection measure for a given industry in a given year, and the variables of interests are the log of the number of workers employed by all trade associations that represent an industry in a year, and the interaction of the latter with log import penetration measured as the ratio of total imports to the value of industrial production. The prevalence index is the total number of measures imposed on all goods in an industry, divided by the total number of goods in that industry. Employee unionization rate refers to ratio of the number of workers that declare to be member of an employee union to the total number of workers in an industry in a given year. The share of nonfinal goods is the number of goods classified as "intermediate" and "capital" goods in the Broad Economic Categories classification divided by the total number of goods in an sector. Industry controls include the number of firms, the number of employees, and total wages in a sector. All specifications include industry and year fixed-effects. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The second potential confounding factor we examine is the possibility that a product's protection from imports may be systematically related to its position in the value chain. As shown by Gawande et al. (2012), once one acknowledges the existence of intermediate inputs, then the determination of trade policy should take into account the possibility of competing interests between downstream producers of a good and upstream firms who use that good as an input, who would have an incentive to lobby against protecting that good. Therefore, sectors whose output is more intensely used in the production of other industries may have lower protection levels than it would be the case if no other organized sectors were interested in keeping its protection low –

which could, as the authors show, explain why early empirical applications based in the Grossman-Helpman framework concluded that the government was more welfare-minded (that is, less prone to taking special interests into consideration) than one might have expected given anecdotal evidence.

Moreover, much of the Brazilian trade protection structure put in place since the mid-XXth century – and only partially dismantled since the late 1980's was based on the principle of "tariff escalation", which, for industrial policy purposes, dictates that the level of protection on finished products should be higher than that of semi-finished products, which in turn should be higher still than that of raw inputs.

In either case, one industry's level of protection may be affected by the relative quantity of final goods and non-final inputs. If the size of the trade association was also correlated to the proportion of non-final inputs among the goods produced by the sector, then the omission of such a variable would bias the results. We therefore include the share of non-final goods[11] among the controls in the two main specifications (equations 3-1 and 3-2).

The results, displayed on columns 3 and 4 of Table 3.4, suggest otherwise. As with the employee unionization rate, the inclusion of the industries' share of non-final goods has virtually no impact on the coefficients or standard errors of the effect of trade association employment or its interaction with import penetration on non-automatic licensing. As for the coefficients of the share of nonfinal goods, point estimates are negative – as one would expect given the mechanism described by Gawande et al. (2012) –, but too imprecisely estimated and statistically indistinguishable from zero.

One possible concern with the empirical strategy so far is the possible endogeneity in the trade association employment variable – in particular the possibility of reverse causation: industries may have powerful political structures due to the fact that they were heavily protected in the past. As mentioned, the ideal way to eliminate this possibility would involve an exogenous change in the association's employment size, which evidently is not empirically feasible. However, we could alleviate the concern with potential endogeneity by using predetermined values of the explanatory variables. The first two columns of table 3.5 present the results with one-period lags of these variables; the estimated coefficients are statistically indistinguishable (if slightly larger) than the counterparts in the previous tables.

Finally, in order to alleviate concerns with potential reverse causation between trade association employment and the level of protection – that is,

[11] Defined as those classified as "intermediate" and "capital" goods in the Broad Economic Categories (BEC) Classification.

the possibility that increases in protection via non-automatic licensing would lead to stronger trade associations, instead of the other way around –, we also control for the forward values of trade association employment. Once again, results – in columns 3 and 4 of Table 3.5 – remain nearly unchanged.

Table 3.5: Robustness: Lags and Leads

	(1)	(2)	(3)	(4)
Variables	Non-Automatic Licensing (Prevalence Index)			
	OLS	OLS	OLS	OLS
Trade Assoc. Employment (t-1)	0.108 (0.039)***	0.245 (0.071)***		
Trade Assoc. Employment (log)			0.079 (0.028)***	0.210 (0.060)***
Trade Assoc. Employment (t+1)			0.030 (0.023)	0.008 (0.032)
Import Penetration (t-1)		-0.040 (0.011)***		
Import Penetration (log)				-0.035 (0.010)***
Trade Assoc. Employment X Import Penetration (t-1)		0.024 (0.007)***		
Trade Assoc. Employment X Import Penetration				0.023 (0.006)***
Trade Assoc. Employment X Import Penetration (t+1)				-0.003 (0.002)
Industry Controls	Yes	Yes	Yes	Yes
Industry and year FE	Yes	Yes	Yes	Yes
Observations	1,229	1,229	1,230	1,230
R-squared	0.307	0.361	0.303	0.349
Number of cnae	88	88	88	88

Notes: This table reports the effect of trade association employment and import penetration on protection measures at industry (3-digit CNAE) level. All columns report the results of OLS panel regressions where the dependent variable is the protection measure for a given industry in a given year, and the variables of interests are the log of the number of workers employed by all trade associations that represent an industry in a year, and the interaction of the latter with log import penetration measured as the ratio of total imports to the value of industrial production, as well as the one-year lags $(t-1)$ and leads $(t+1)$ of these variables. The prevalence index is the total number of measures imposed on all goods in an industry, divided by the total number of goods in that industry. Industry controls include the number of firms, the number of employees, and total wages in a sector. All specifications include industry and year fixed-effects. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.5
Addressing Endogeneity in Import Penetration

Our empirical exercise so far relied on the reasoning that controlling for Chinese imports penetration and its interaction with the trade association capacity variable would capture the industries' "lobbying together" (as in Bombardini and Trebbi (2012)) for trade protection in a circumstance of heightened competition with foreign products, hence isolating this trade policy motive for larger trade associations from a host of other confounders.

An obvious concern with this strategy is that this measure of the need for protection is directly related to Brazilian imports from China, whose behavior may be capturing the effect of other phenomena, such as industry-level shocks. Therefore, the measure may be correlated with the error term, resulting in biased estimates. In order to deal with this issue, we instrument the penetration of Chinese imports with another measure of import penetration which replaces the (probably endogenous) bilateral trade flows by a (plausibly exogenous) "counterfactual" trajectory of these flows obtained by multiplying baseline trade levels with the excess growth rate of China's exports in a given sector in comparison with the world average. Following Costa et al. (2016), this Chinese excess growth rate is obtained from the following set of auxiliary regressions:

$$\frac{X^*_{cit} - X^*_{ci0}}{X^*_{ci0}} = \tau_{it} + \delta_{China,it} + \zeta_{cit}$$

where X^*_{cit} is industry i's exports of country c to all countries except Brazil. One set of regressions is run for every year, keeping fixed the baseline trade values, which are also used as weights in all regressions.

The industry fixed effects, τ_{it}, capture the sector's average export growth rate across all countries (except Brazil) from the baseline year to year t, thus accounting for world-level shocks. The China dummies $\delta_{China,it}$, therefore, capture the deviation in growth rates of Chinese trade in industry i from this countrywide average – that is, the excess contribution of China to the growth rate of world exports in that sector.

The "counterfactual" value of Brazilian imports of industry i's products from China at a given year t are then given by $\hat{I}_{it} = I_{i0}(1 + \delta_{China,i})$. The instrumental variable for a given year's import penetration is, therefore, the ratio of this counterfactual level of imports from China ($\hat{I}_{it}$) to the baseline year's value of industrial production.

Table 3.6: Trade Association Employment, Import Penetration and Protection Measures

Variables	(1)	(2)	(3)	(4)	(5)
	Non-Automatic Licensing (Prevalence Index)				
	IV	IV	IV	IV	IV
Trade Assoc. Employment (log)	0.274 (0.081)***	0.270 (0.081)***	0.433 (0.161)***	0.255 (0.082)***	0.251 (0.083)***
Trade Assoc. Employment (t+1)			-0.190 (0.154)		
Employee Unionization Rate				0.155 (0.085)*	
Share of Nonfinal Goods					-0.091 (0.121)
Import Penetration (log)	-0.015 (0.017)	-0.025 (0.016)	-0.010 (0.016)	-0.019 (0.016)	-0.019 (0.016)
Trade Assoc. Employment X Import Penetration	0.030 (0.009)***	0.029 (0.009)***	0.058 (0.025)**	0.027 (0.009)***	0.026 (0.009)***
Trade Assoc. Employment X Import Penetration (t+1)			-0.035 (0.025)		
Industry Controls	No	Yes	Yes	Yes	Yes
Industry and year FE	Yes	Yes	Yes	Yes	Yes
Observations	1,372	1,323	1,230	1,309	1,323
R-squared	0.294	0.326	0.202	0.330	0.327
Number of cnae	88	88	88	88	88

Notes: This table reports the effect of trade association employment and import penetration on protection measures at industry (3-digit CNAE) level. All columns report the results of 2SLS panel regressions where the regressand is the protection measure for a given industry in a given year, and the variables of interests are the log of the number of workers employed by all trade associations that represent an industry in a year, and the interaction of the latter with log import penetration (measured as the ratio of total imports to the value of industrial production). The instrumental variable is the excess contribution of China to the growth rate of world exports in a given sector. The prevalence index is the total number of measures imposed on all goods in an industry, divided by the total number of goods in that industry. Employee unionization rate refers to ratio of the number of workers that declare to be member of an employee union to the total number of workers in an industry in a given year. The share of nonfinal goods is the number of goods classified as "intermediate" and "capital" goods in the Broad Economic Categories classification divided by the total number of goods in an sector. Industry controls include the number of firms, the number of employees, and total wages in a sector. All specifications include industry and year fixed-effects. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3.6 presents the two-stage least squares estimates using the instrument for import penetration, including also (in the last three columns) specifications that control for the additional variables addressed in the previous section. It is noticeable that the point estimates are larger than the corresponding ones from the previous sections, suggesting that the latter may be downward biased – although the difference isn't statistically significant. The implied relative magnitude of the main effect of trade association employment on the prevalence of non-automatic licenses is not much larger than that obtained previously: considering the main specification on column (2), increasing employment by one standard deviation from the main would result in an increase of 18% of a standard deviation in licensing (against 15% in the OLS estimate). The increase in the magnitude of the effect of the interaction term is more marked: comparing the percentiles 75 and 25 of import penetration now increases the effect of employment on licensing by 152% (against the 112% previously found).

3.6 Productivity and Trade Association Capacity

In the previous sections, we have presented data supporting the hypothesis that industries which are capable of building stronger trade associations are able to increase their protection from imports through non-automatic licensing, especially when imports surge. The question remains, however, of why would some industries have stronger organized representation structures than others. A full answer to these question would involve a myriad of factors, from collective bargaining issues to the regulatory environment, and is outside of the scope of this research. Nevertheless, in this section we present suggestive evidence of a possible link between industry-level changes in productivity and trade association capacity building.

Such a relationship could arise in a framework in which firms decide on how to allocate their resources between internal cost-reducing activities, at one hand, and politically-oriented activities destined to influence policymakers to implement policies that benefit the entire industry, at the other – such as Hillman (1991) or Hillman et al. (2001), for example. Then, firm or sector-level differences in comparative advantage in lobbying for protection may influence this relationship between productivity and investment in political capacity. We could also draw an analogy with the model in Brainard and Verdier (1997), in which lobbying for protection is a substitute for costly adjustment from the point of view of an import-competing firm that receives a negative shock.

Thus, we first regress the long difference (that is, 2014-1999) of log trade association employment on the long difference of log productivity (measured by the ratio of the value of industrial transformation to the value of labor compensation from PIA[12]). Alternatively, to smooth yearly abrupt changes,

[12]Using the gross value of industrial production instead of transformation yields qualitatively similar but less precisely estimated results, presented in the Appendix.

we also use the differences between the averages of the first four and last four years in our sample (ie, the 1999-2002 and the 2011-2014 averages). The results, presented in Table 3.7, point to a negative correlation between the two variables: industries with larger decreases in productivity have increased their trade association staffs. The relative magnitudes imply that an decrease of one standard deviation in the former is associated with an increase of only about one quarter of a standard deviation in the latter.

Table 3.7: Productivity and Trade Association Employment

	(1)	(2)
	Trade Association Employment (log)	
Variables	Last - First	Avg. Last 4 - Avg First 4
Productivity (log)	-0.446 (0.148)***	-0.348 (0.166)**
Observations	84	85
R-squared	0.065	0.050

Notes: This table reports the effect of industry productivity on trade association employment at the industry (3-digit CNAE) level. Column 1 reports the results from an OLS regression where the regressand is the 2014-1999 difference in the log of the number of workers employed by all trade associations that represent an industry, and the regressor is the 2014-1999 difference in log productivity measured as the ratio of total imports to the value of industrial production. Column 2 reports the results from a similar OLS regression where we use the differences between the averages of the last four (2011-2014) and first four (1999-2002) years of the sample. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Second, we regress log trade association employment on log productivity in a panel setting, including industry and year fixed-effects. Results (table 3.8 corroborate the previously found negative relationship between productivity and trade association employment, although with smaller magnitudes. The result is maintained if we control for industry-level characteristics (number of firms, employment and employee unionization rates), and also if we use lagged values of productivity.

Table 3.8: Productivity and Trade Association Employment - Panel

	(1)	(2)	(3)	(4)
Variables	Trade Association Employment (log)			
Productivity (log)	-0.170 (0.070)**	-0.175 (0.075)**		
Productivity (log) (t-1)			-0.149 (0.073)**	-0.151 (0.077)*
Industry and year FE	Yes	Yes	Yes	Yes
Industry-level controls	No	Yes	No	Yes
Observations	1,372	1,309	1,278	1,215
R-squared	0.061	0.070	0.046	0.057
Number of cnae	88	88	88	88

Notes: This table reports the effect of industry productivity on trade association employment at the industry (3-digit CNAE) level. All columns report the results from OLS panel regressions where the regressand is the log of the number of workers employed by all trade associations that represent an industry in a given year, and the regressor is the log of industry productivity (measured as the ratio of total imports to the value of industrial production) in a year (columns 1-2), or it's one-year lag (columns 3-4). Industry controls include the number of firms, the number of employees, and total wages in a sector. All specifications include industry and year fixed-effects. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Finally, we include the aforementioned measure of industry-level productivity as a control in our main regressions discussed in the previous sections (equations 3-1 and 3-2). Results in Table 3.9 point to a negative relationship between productivity and the prevalence of non-automatic licenses; the remaining estimates, however, remain mostly unchanged *vis-à-vis* the ones without controlling for productivity.

Table 3.9: Productivity, Trade Association Employment and Licensing

VARIABLES	(1)	(2)	(3)	(4)
	Non-Automatic Licensing (Prevalence Index)			
	OLS	OLS	OLS	IV
Trade Assoc. Employment (log)	0.091	0.090	0.218	0.264
	(0.039)**	(0.037)**	(0.068)***	(0.081)***
Productivity	-0.076	-0.072	-0.082	-0.089
	(0.039)*	(0.036)*	(0.037)**	(0.040)**
Import Penetration (log)			-0.041	-0.020
			(0.010)***	(0.016)
Trade Assoc. Employment X			0.023	0.029
Import Penetration			(0.006)***	(0.009)***
Industry Controls	No	Yes	Yes	Yes
Industry and year FE	Yes	Yes	Yes	Yes
Observations	1,372	1,323	1,323	1,323
R-squared	0.288	0.309	0.365	0.327
Number of cnae	88	88	88	88

Notes: This table reports the effect of trade association employment and import penetration on protection measures at industry (3-digit CNAE) level. All columns report the results of OLS or 2SLS panel regressions where the regressand is the protection measure for a given industry in a given year, and the variables of interests are the log of the number of workers employed by all trade associations that represent an industry in a year, and the interaction of the latter with log import penetration (measured as the ratio of total imports to the value of industrial production). The instrumental variables is the excess contribution of China to the growth rate of world exports in a given sector. The prevalence index is the total number of measures imposed on all goods in an industry, divided by the total number of goods in that industry. Productivity is measured as the ratio of the value of industrial transformation to the value of labor compensation. Industry controls include the number of firms, the number of employees, and total wages in a sector. All specifications include industry and year fixed-effects. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

3.7 Concluding Remarks

This paper examines whether industries with higher capacity of political organization are able to obtain more protection from foreign competitors. To circumvent the lack of direct evidence on special interest politics and lobbying activity in Brazil, we use a novel dataset on trade associations' characteristics, based on the hypothesis that firms in a given industry may join forces in a sectoral representation structure, particularly when the policy in question is determined at the industry level – which is frequently the case in trade policy.

The evidence presented suggests that industries with larger trade associations obtain more protection, particularly through non-automatic licensing, which is often used as a form of short-term protection from import surges. This effect is robust to the inclusion of control variables related to employee unionization – which could affect the size of trade associations for reasons other than trade policy – and to the share of nonfinal goods in the sector – which could affect its level of protection.

Moreover, the estimated effects are magnified when firms are in greater need for protective measures – that is, when import penetration increases more intensely. This latter effect is robust to addressing possible endogeneity of the import penetration measure by an instrumental variables strategy that turns to the "China shock" as a natural experiment that generated plausibly exogenous variation in imports from China.

Finally, we also present suggestive evidence that the variation in trade association size may be inversely related to the evolution of an industry's productivity, which is consistent with industries turning to rent-seeking activities when their competitiveness is lacking, in consonance with a framework in which lobbying for protection is a substitute for cost-reducing activities or costly adjustment to negative shocks.

Evidently, the empirical strategy adopted in this paper is not without its limitations; these, however, may be useful guides for directions in future research. One of the main concerns in identifying the effects of trade association size on import protection is, as discussed, the possibility of reverse causation – that is, industries may have powerful political structures due to the fact that they were protected in the past. Future research should, therefore, be pointed to achieving a more robust identification in this regard, possibly by the use of an instrument for trade association size. Other possible path would be to add more structure to the problem, devising a framework for the relationship between industry associations and trade policy determination.

The evidence obtained in this chapter point to a relevant channel in the endogenous determination of trade policy that shoud be better acknowledged in the determination of trade policymaking structures. In particular, two issues stand out. First, results showing that industries organize themselves to obtain protection from import surges through import licensing suggest that, at least in the time frame of this paper, this measure may have been misused as trade defence measures, instead of other policy instruments specifically for this purpose. Moreover, the evidence also suggests that highly discretionary measures with dispersed competence – which is the case of non-automatic licenses – seem more prone to capture by industry special interests than those that are subject to a more complex and high-level implementation process.

Final Remarks

The objective of this thesis is to analyze the distributional effects of trade, as well as the political economy of protection that arises from these effects, by focusing on a specific trade shock: the rise of China as major trading power, following a series of reforms that transformed its economic structure and enhanced its productivity. The three chapters that compose this thesis assess the effects of this shock on wage inequality, on employment dynamics, and on the effectiveness of lobbying activities by industry-level associations in order to block foreign competitors.

The first chapter shows that the export-demand side of the China shock may have contributed to the reduction in wage inequality in the tradables sector; this effect seems to have manifested itself through the between-firms component of wage dispersion, and stemmed from changes in firm behavior, rather than composition effects. Moreover, this change in behavior appears to be related to a compression in the exporter wage premium – that is, although exporter firms on average pay higher wages across the whole period, this higher wage conditional on firm exporting status seems to have been negatively affected by the external demand shock.

Also in the first chapter I employ a structural framework developed by Helpman et al. (2017) to further examine the relationship between foreign demand, the exporter wage premium, and wage inequality, performing counterfactual exercises that explore sectoral-level differences in the foreign demand shock, which affected distinctly across sectors the evolution of the ratio of foreign to domestic demand. The exercise suggests that the China demand shock can explain part of the observed aggregate reduction in the exporter wage premium and in wage dispersion.

In the second chapter, I develop a version of the dynamic trade model by Caliendo et al. (2019) in order to estimate the effects of the dual China shock on the sectoral dynamics of Brazilian employment. The model structure incorporates empirically relevant features such as intermediate consumption, input-output linkages between sectors, productivity differentials at the country and firm levels, nontradable sectors and mobility costs that preclude immediate adjustment of the labor force in the face of price and wage changes; the evidence provided by the counterfactual exercise suggests that both shocks lead to a contraction in most manufacturing sectors, and an expansion in most services sectors, but the general equilibrium effects of the shocks are modest, especially if compared to an alternative counterfactual in which Brazilian productivity in primary sectors increase. Using an extended the model that includes two types of labor – skilled and unskilled –, the counterfactuals also point to small distributional effects of the China shock, but consistent with reduced-form evidence obtained in Chapter 1, with the import shock reducing the share of unskilled workers in the nontradables sectors and increasing in the tradables sectors, and the export shock leading to an even smaller effect on the relative demand for labor types.

In the final chapter I turn to the political economy of trade policy and how it responds to an import competition shock. First, to circumvent the lack of direct data on lobbying activities, I build a novel dataset on Brazilian trade associations' characteristics in order to investigate whether industries with higher capacity of political organization are able to obtain more protection from foreign competitors. I use variation in import penetration as a measure of the need for trade protection, and address endogeneity on this measure by using an instrumental variables strategy based on the China import shock. Evidence suggests that industries with larger employer unions are able to obtain more protection, particularly through non-automatic licensing; the estimates suggest that this effect is higher when import penetration increases more intensely, which is interpreted as increased need for protective measures. The effect is robust to a host of controls such as worker unions' sizes or share of intermediate products in a given industry. Evidence also suggests that the variation in trade association size may be inversely related to the evolution of an industry's productivity, which could indicate that industries struggling with lack of efficiency may turn to rent-seeking activities – which would be consistent with a framework in which lobbying for protection is a substitute for cost-reducing activities or costly adjustment to negative shocks.

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A
Appendix to Chapter 1

A.1
Additional Results

In this Appendix, we present a number of additional results that reinforce or complement some points made in the main text of Chapter 1. First, we complement the discussion on the effects of the China Shock on informality by looking at the effects on informality in each sector, tradables and nontradables (table A.1). It appears that the increase in formal contracts caused by the export shock happened in the tradables sector, while the corresponding decrease in informality and self-employment happened in the nontradables sector – that is, the increase in exports induced by the rise of China has led to a shift in the labor force from informal jobs in the nontradables sector to formal jobs the tradables sector. The estimates of the effect of the import shock, albeit less precise, suggest that the reduction in informality may have happened in both sectors.

Table A.1: Effects on Informality – Tradables vs. Nontradables

2010-00 diff. in:	(1) Formal Employees (Tradables) / Occupied	(2) Informal Employees (Tradables) / Occupied	(3) Self-Employed (Tradables) / Occupied	(4) Formal Employees (Nontradables) / Occupied	(5) Informal Employees (Nontradables) / Occupied	(6) Self-Employed (Nontradables) / Occupied
XD	0.003	0.000	-0.001	0.001	-0.003	-0.001
	(0.001)**	(0.001)	(0.001)	(0.001)	(0.001)***	(0.001)*
IS	0.005	-0.005	0.001	0.004	-0.005	-0.001
	(0.006)	(0.003)*	(0.002)	(0.003)	(0.003)*	(0.002)
State FE	yes	yes	yes	yes	yes	yes
Dem. Controls	yes	yes	yes	yes	yes	yes
Observations	413	413	413	413	413	413
R-squared	0.237	0.528	0.306	0.295	0.635	0.394

Clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In table A.1, we focused on formal and informal labor in tradables and nontradables as a share of the total workforce. A different way to look at the effects on informality on each sector is to look at formal and informal workers as a share of the sector's workforce only; table A.2, displays these results. It shows that, while in the tradables sector the export shock induced a movement both from informal and self-employed labor to formal employment, in the nontradables sector both formality and self-employment have risen.

Table A.2: Effects on Informality – Tradables vs. Nontradables

	(1)	(2)	(3)	(4)	(5)	(6)
	Occupied (Tradables)			Occupied (Nontradables)		
2010-00 diff. in:	Formal Employees	Informal Employees	Self-Employed	Formal Employees	Informal Employees	Self-Employed
XD	0.008	-0.005	-0.005	0.003	-0.002	0.004
	(0.003)***	(0.002)**	(0.002)**	(0.001)**	(0.001)**	(0.002)**
IS	0.012	-0.007	-0.000	0.009	-0.008	0.001
	(0.010)	(0.006)	(0.004)	(0.004)**	(0.005)	(0.005)
State FE	yes	yes	yes	yes	yes	yes
Dem. Controls	yes	yes	yes	yes	yes	yes
Observations	413	413	413	413	413	413
R-squared	0.269	0.410	0.240	0.409	0.572	0.225

Clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.3 presents the effects on log employment of firms by average wage percentiles. Results suggest that the export shock has led to an increase in employment of high-paying firms both for tradables and nontradables, and a reduction in employment of firms in the middle portion of the distribution for nontradables. The implied magnitudes are similar to the ones for employment shares: comparing microregions in the 90th and 10th percentiles of shock intensity, the effect on tradables' p90 is around 15% of a standard deviation of the overall difference, while for nontradables the corresponding figures are 10% of a SD for the p90 and 20% for the negative effect on p50. The import shock seems to have affected only nontradables, and particularly the bottom part of the distribution, with even higher magnitude, of almost 30% of a standard deviation for the 10th percentile. In sum, the results are similar to those found for employment shares; the exception is the effect of the export shock on employment of nontradables' firms in the 90th percentile, which do not translate to an increase in employment share.

Table A.3: Effects on Employment by Avg. Wage Percentiles – Stayer Firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All Sectors			Nontradables			Tradables		
2010-00 diff. in:	p90	p50	p10	p90	p50	p10	p90	p50	p10
Panel A: log employment of pctile of observed (log) wages									
XD	0.066	-0.203	0.012	0.054	-0.231	0.011	0.141	-0.077	0.053
	(0.021)***	(0.069)***	(0.037)	(0.019)***	(0.072)***	(0.035)	(0.049)***	(0.062)	(0.037)
IS	0.112	0.175	0.176	0.068	0.231	0.179	-0.092	0.185	0.002
	(0.050)**	(0.093)*	(0.070)**	(0.046)	(0.119)*	(0.058)***	(0.106)	(0.126)	(0.113)
R-sq.	0.156	0.196	0.408	0.149	0.482	0.533	0.090	0.105	0.220
Panel B: log employment of pctile of residual wages									
XD	0.022	0.026	-0.003	0.010	0.030	-0.006	0.058	-0.059	0.004
	(0.028)	(0.022)	(0.019)	(0.019)	(0.024)	(0.016)	(0.044)	(0.045)	(0.036)
IS	0.055	0.049	0.043	0.048	0.037	0.014	-0.120	0.212	0.076
	(0.066)	(0.057)	(0.060)	(0.051)	(0.059)	(0.052)	(0.123)	(0.108)*	(0.101)
R-sq.	0.183	0.208	0.196	0.179	0.205	0.232	0.121	0.200	0.198
Obs.	413	413	413	413	413	413	402	402	402

All specifications include state fe, demographic controls and lagged level of dependent variable. Clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Tables A.5 and A.4 show that, if we fix the firm ranking according to the wage distribution in 2000, virtually all the effects vanish – as is the case with average wages.

Table A.4: Effects on Employment Share by Avg. Wage Percentiles – Stayer Firms, Pctiles fixed in base year

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All Sectors			Nontradables			Tradables		
2010-00 diff. in:	p90	p50	p10	p90	p50	p10	p90	p50	p10
Panel A: employment share of pctile of observed (log) wages									
XD	-0.001	0.002	0.000	0.001	0.000	0.001	0.001	-0.001	-0.002
	(0.003)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.005)	(0.002)	(0.002)
IS	0.011	-0.001	0.002	-0.006	-0.003	0.001	0.012	-0.001	0.013
	(0.009)	(0.003)	(0.004)	(0.005)	(0.003)	(0.002)	(0.015)	(0.004)	(0.010)
R-sq.	0.090	0.141	0.147	0.145	0.122	0.207	0.118	0.114	0.067
Panel B: employment share of pctile of residual wages									
XD	-0.004	-0.000	-0.001	-0.001	0.001	-0.000	-0.001	-0.001	-0.000
	(0.002)*	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.004)	(0.002)	(0.001)
IS	0.002	-0.000	-0.000	-0.001	0.008	-0.001	0.010	0.000	0.011
	(0.008)	(0.005)	(0.003)	(0.005)	(0.005)	(0.003)	(0.010)	(0.005)	(0.008)
R-sq.	0.065	0.092	0.062	0.061	0.088	0.088	0.202	0.083	0.079
Obs.	413	413	413	413	413	413	399	399	399

All specifications include state fe, demographic controls and lagged level of dependent variable. Clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.5: Effects on Employment by Avg. Wage Percentiles – Stayer Firms, Pctiles fixed in base year

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All Sectors			Nontradables			Tradables		
2010-00 diff. in:	p90	p50	p10	p90	p50	p10	p90	p50	p10
Panel A: log employment of pctile of observed (log) wages									
XD	0.014	0.011	0.019	0.007	0.026	0.034	0.026	0.047	-0.031
	(0.012)	(0.020)	(0.015)	(0.010)	(0.017)	(0.017)**	(0.022)	(0.051)	(0.031)
IS	0.054	0.093	0.026	0.062	0.000	0.035	-0.004	0.077	0.054
	(0.049)	(0.063)	(0.044)	(0.044)	(0.047)	(0.029)	(0.078)	(0.088)	(0.074)
R-sq.	0.317	0.102	0.186	0.407	0.165	0.190	0.210	0.142	0.191
Panel B: log employment of pctile of residual wages									
XD	0.012	0.004	-0.001	-0.005	0.010	0.026	0.001	0.002	0.017
	(0.027)	(0.011)	(0.018)	(0.023)	(0.012)	(0.023)	(0.039)	(0.035)	(0.041)
IS	0.084	0.054	0.056	0.013	0.039	0.002	0.050	0.144	0.235
	(0.047)*	(0.053)	(0.062)	(0.042)	(0.051)	(0.051)	(0.078)	(0.094)	(0.114)**
R-sq.	0.213	0.208	0.089	0.198	0.234	0.107	0.167	0.221	0.157
Obs.	413	413	413	413	413	413	399	399	399

All specifications include state fe, demographic controls and lagged level of dependent variable. Clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Tables A.6 and A.7 present the effects on log employment by average wage percentiles, restricting the samples to firms that move along the average wage distribution and those that do not. Results are also similar to those for employment shares.

Table A.6: Effects on Employment by Avg. Wage Percentiles – Firms that Change Avg. Wage Quintile

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All Sectors			Nontradables			Tradables		
2010-00 diff. in:	p90	p50	p10	p90	p50	p10	p90	p50	p10
Panel A: log employment of pctile of observed (log) wages									
XD	0.055	-0.329	0.051	0.077	-0.350	0.063	-0.056	-0.131	0.037
	(0.034)	(0.118)***	(0.037)	(0.027)***	(0.141)**	(0.036)*	(0.065)	(0.074)*	(0.046)
IS	-0.061	0.064	0.173	-0.099	0.130	0.187	0.170	-0.168	0.047
	(0.058)	(0.158)	(0.088)**	(0.054)*	(0.160)	(0.074)**	(0.128)	(0.161)	(0.158)
R-sq.	0.132	0.246	0.430	0.156	0.270	0.520	0.113	0.102	0.245
Panel B: log employment of pctile of residual wages									
XD	0.012	0.053	-0.004	0.036	0.037	-0.011	0.043	-0.090	0.013
	(0.033)	(0.029)*	(0.024)	(0.036)	(0.028)	(0.023)	(0.056)	(0.054)*	(0.046)
IS	0.002	0.069	0.071	0.057	0.068	0.072	-0.052	0.136	0.089
	(0.094)	(0.053)	(0.072)	(0.077)	(0.076)	(0.064)	(0.157)	(0.160)	(0.114)
R-sq.	0.119	0.160	0.212	0.125	0.232	0.244	0.152	0.178	0.236
Obs.	413	413	413	413	413	413	399	399	399

All specifications include state fe, demographic controls and lagged level of dependent variable. Clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.7: Effects on Employment by Avg. Wage Percentiles – Firms that Stay in Avg. Wage Quintile

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All Sectors			Nontradables			Tradables		
2010-00 diff. in:	p90	p50	p10	p90	p50	p10	p90	p50	p10
Panel A: log employment of pctile of observed (log) wages									
XD	0.012	0.035	-0.044	-0.015	-0.023	-0.054	0.036	-0.035	-0.036
	(0.033)	(0.036)	(0.029)	(0.035)	(0.029)	(0.030)*	(0.078)	(0.064)	(0.034)
IS	0.011	0.044	0.194	0.072	0.140	0.175	-0.149	0.053	0.083
	(0.064)	(0.083)	(0.075)***	(0.085)	(0.069)**	(0.147)	(0.167)	(0.165)	(0.091)
R-sq.	0.116	0.194	0.274	0.106	0.167	0.282	0.114	0.140	0.129
Panel B: log employment of pctile of residual wages									
XD	-0.007	0.007	-0.026	-0.002	-0.007	-0.048	0.123	-0.013	0.034
	(0.039)	(0.035)	(0.024)	(0.040)	(0.041)	(0.021)**	(0.071)*	(0.061)	(0.049)
IS	0.130	-0.038	-0.106	0.130	-0.001	-0.046	-0.037	0.274	0.025
	(0.085)	(0.090)	(0.050)**	(0.081)	(0.071)	(0.046)	(0.150)	(0.131)**	(0.080)
R-sq.	0.146	0.185	0.182	0.125	0.169	0.193	0.169	0.123	0.149
Obs.	409	409	409	409	409	409	374	374	374

All specifications include state fe, demographic controls and lagged level of dependent variable. Clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.8 presents the estimates of the effects of the China shock on firm average wages for all sectors and for nontradables.

Table A.8: Results using Firm Avg Wages – Full Sample and Nontradables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full Sample				Nontradables			
2010-00 diff. in:	Var.	p90-p10 gap	p90-p50 gap	p50-p10 gap	Var.	p90-p10 gap	p90-p50 gap	p50-p10 gap
Panel A: observed (log) wages								
XD	-0.001	-0.006	-0.011	0.005	0.002	0.024	0.018	0.007
	(0.004)	(0.012)	(0.012)	(0.008)	(0.004)	(0.014)*	(0.010)*	(0.008)
IS	-0.016	-0.046	-0.059	0.014	-0.007	-0.016	-0.031	0.013
	(0.011)	(0.048)	(0.045)	(0.011)	(0.012)	(0.044)	(0.038)	(0.014)
R-squared	0.253	0.207	0.191	0.236	0.335	0.223	0.192	0.227
Panel B: residual wages								
XD	-0.003	-0.006	-0.007	0.002	0.001	0.010	0.009	0.001
	(0.002)	(0.010)	(0.009)	(0.004)	(0.002)	(0.010)	(0.010)	(0.004)
IS	-0.014	-0.052	-0.060	0.007	-0.011	-0.023	-0.022	0.001
	(0.008)*	(0.038)	(0.037)	(0.010)	(0.008)	(0.035)	(0.031)	(0.011)
R-squared	0.327	0.237	0.184	0.249	0.429	0.271	0.280	0.162
Obs.	408	408	408	408	408	408	408	408

All specifications include state fe, demographic controls and lagged level of dependent variable. Clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.1.0.1
Effects of Trade Shocks on Firm Average Wage Percentiles

This subsection examines the effects not on the gaps between percentiles of firm average wages but on the percentiles themselves – that is, on the 2010-2000 difference between the *values* of the 90th, 50th and 10th percentiles. Since the main goal of this exercise is to gather evidence in order to illuminate whether the reduction in between-firm wage dispersion is due to firm behavior or composition, we abstract from changes in the firm pool, focusing solely on the balanced panel.

The results on table (A.9) show that, in consonance with the idea of a change in behavior of firms, the export shock has contributed to an increase in the wages of low-paying firms (that is, those in the percentile 10 of the average wage distribution) and a decrease in the wages of high-paying firms (percentile 90) for tradables (columns 7 and 9), respectively. The magnitudes of the effects are also in line with previous results: using the same comparison previously mentioned between microregions in the 90th and 10th percentiles of the shock, the effects on both percentiles are around one fifth of a standard deviation of the overall difference in each variable, either for observed or residual wages.

Unlike previous results, however, the effects are not restricted to the tradables sector: the export shock has also contributed to an increase in wages across all distribution – the magnitudes are similar for the three percentiles (ranging between 9% and 16% of a SD), which could explain why there is no effect on the inequality measures, since all portions of the wage distribution seem to have responded in tandem. These results are reflected in those for the full sample: the average wages of firms in percentiles 10 and 50 increase with the export shock, while the opposing effects on p90 for each sector lead to no visible effect in the whole sample.

Finally, the import shock also seems to play a role: the coefficients for its effect on all parts of the wage distribution in all sectors are negative, although only statistically significant for the middle and top portions for tradables.

Table A.9: Effects on Avg. Wage Percentiles – Stayer Firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All Sectors			Nontradables			Tradables		
2010-00 diff. in:	p90	p50	p10	p90	p50	p10	p90	p50	p10
Panel A: observed (log) wages									
XD	-0.013	0.017	0.008	0.047	0.019	0.009	-0.070	0.001	0.028
	(0.013)	(0.009)*	(0.003)**	(0.023)**	(0.008)**	(0.004)**	(0.033)**	(0.017)	(0.011)**
IS	-0.047	-0.018	-0.005	-0.005	-0.031	-0.010	-0.091	-0.065	-0.004
	(0.055)	(0.011)	(0.011)	(0.056)	(0.027)	(0.010)	(0.052)*	(0.027)**	(0.026)
R-squared	0.265	0.591	0.853	0.258	0.527	0.881	0.192	0.437	0.610
Panel B: residual wages									
XD	0.003	0.015	0.013	0.034	0.016	0.013	-0.047	0.010	0.026
	(0.010)	(0.009)*	(0.005)**	(0.016)**	(0.007)**	(0.004)***	(0.025)*	(0.014)	(0.011)**
IS	-0.088	-0.021	-0.013	-0.046	-0.023	0.000	-0.103	-0.047	-0.006
	(0.052)*	(0.012)*	(0.011)	(0.047)	(0.021)	(0.009)	(0.048)**	(0.020)**	(0.021)
R-squared	0.231	0.397	0.618	0.202	0.385	0.627	0.199	0.241	0.381
Obs.	413	413	413	413	413	413	402	402	402

All specifications include state fe, demographic controls and lagged level of dependent variable. Clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The results presented in table (A.9) focus on the behavior of firms in each portion of the wage distribution, attributing firms to percentiles according to each year's distribution. That is, we compare the average wages of, say, high paying firms in 2000 with that of high-paying firms in 2010, which may or may not be the same firms – even though the set of firms is the same in both years, there could have been movement of firms along the wage distribution between the two years. Thus, next we examine whether this movement of firms along the average wage distribution contributes to the results, or these are driven by average wage changes by the same firms.

The first way to do this is to simply assign firms to percentiles of the wage distribution in the base year and examine the difference in average wages practiced by these firms between the two years. That is, instead of comparing, for example, the average wages of high-paying firms in 2000 to that of high-paying firms in 2010, we compare the average wages of 2000's high-paying firms in 2000 to that of these same firms in 2010.

Table A.10: Effects on Avg. Wage Percentiles – Percentiles fixed in base year

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		All Sectors			Nontradables			Tradables	
2010-00 diff. in:	p90	p50	p10	p90	p50	p10	p90	p50	p10
Panel A: observed (log) wages									
XD	-0.002	0.012	0.010	0.004	0.014	0.010	0.019	0.006	0.001
	(0.006)	(0.006)**	(0.005)**	(0.006)	(0.006)**	(0.004)**	(0.014)	(0.007)	(0.007)
IS	0.016	-0.011	-0.043	-0.003	0.001	-0.051	-0.012	0.011	-0.028
	(0.012)	(0.010)	(0.022)**	(0.011)	(0.012)	(0.022)**	(0.022)	(0.019)	(0.019)
R-squared	0.661	0.821	0.664	0.690	0.839	0.659	0.409	0.657	0.554
Panel B: residual wages									
XD	0.002	0.012	0.009	0.004	0.013	0.006	0.007	0.012	0.014
	(0.005)	(0.006)**	(0.006)	(0.005)	(0.006)**	(0.005)	(0.014)	(0.011)	(0.012)
IS	0.008	-0.011	0.007	-0.004	0.000	0.012	0.024	0.031	0.005
	(0.016)	(0.016)	(0.013)	(0.013)	(0.013)	(0.015)	(0.017)	(0.021)	(0.022)
R-squared	0.387	0.547	0.452	0.345	0.581	0.439	0.322	0.367	0.339
Obs.	409	405	412	406	397	412	351	344	372

All specifications include state fe, demographic controls and lagged level of dependent variable. Clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The results, displayed in Table (A.10), suggest that, at least for tradables, the results seem mainly driven by the movement of firms along the average wage distribution: the estimated coefficients here are much smaller than those of table (A.9), and all statistically insignificant. Only the effect on the middle and bottom percentiles for nontradables are still significant and comparable in magnitude to those found in table (A.9).

Another way of assessing the role of the movement of firms along the average wage distribution is to divide each sample in two subsets: the *movers* (the firms that occupied a different quintile of the 2010's wage distribution than the one it occupied in the 2000's wage distribution) and the non-movers (the firms that are in the same quintile in the both years' wage distributions, which comprise approximately 5% of the total[1]).

[1]More and less strict definitions of movers and non-movers – considering deciles and terciles of the wage distribution, respectively – yield similar results.

Table A.11: Effects on Avg. Wage Percentiles – Firms that Change Avg. Wage Quintile

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All Sectors			Nontradables			Tradables		
2010-00 diff. in:	p90	p50	p10	p90	p50	p10	p90	p50	p10
Panel A: observed (log) wages									
XD	0.059	0.022	0.007	0.039	0.016	0.004	0.039	0.042	0.017
	(0.028)**	(0.009)**	(0.004)*	(0.028)	(0.010)	(0.005)	(0.054)	(0.014)***	(0.006)***
IS	-0.129	-0.011	-0.015	-0.062	-0.016	-0.008	-0.062	-0.027	-0.036
	(0.071)*	(0.014)	(0.014)	(0.070)	(0.017)	(0.012)	(0.063)	(0.051)	(0.033)
R-squared	0.326	0.679	0.813	0.354	0.625	0.834	0.199	0.293	0.552
Panel B: residual wages									
XD	0.043	0.016	0.012	0.025	0.016	0.013	0.049	0.033	0.013
	(0.017)**	(0.007)**	(0.005)**	(0.018)	(0.007)**	(0.005)***	(0.028)*	(0.013)***	(0.008)*
IS	-0.084	-0.012	-0.011	-0.072	-0.005	0.001	-0.031	-0.019	-0.042
	(0.065)	(0.013)	(0.012)	(0.064)	(0.017)	(0.013)	(0.041)	(0.037)	(0.029)
R-squared	0.268	0.425	0.500	0.278	0.472	0.490	0.139	0.204	0.346
Obs.	413	413	413	413	413	413	399	399	399

All specifications include state fe, demographic controls and lagged level of dependent variable. Clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table (A.11) presents the results for the subset of firms that move along the wage distribution between 2000 and 2010. Results are roughly similar to those of table (A.9); the main difference is that the effect of the trade shock on the 90th percentile for tradables is insignificant for observed wages, and positive and significant at the 10% level for residual wages.

As for the firms that appear in the same quintile of the wage distribution of both years, the results for the tradables sector are starkly different: the estimates for the 10th percentile are insignificant, and those for the percentile 90 (and p50 for observed wages) are negative and significant, with relative magnitudes similar to those of the main results.

Table A.12: Effects on Avg. Wage Percentiles – Firms that Stay in Avg. Wage Quintile

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All Sectors			Nontradables			Tradables		
2010-00 diff. in:	p90	p50	p10	p90	p50	p10	p90	p50	p10
Panel A: observed (log) wages									
XD	-0.022	0.013	0.021	-0.027	0.002	0.019	-0.057	-0.040	0.015
	(0.018)	(0.013)	(0.005)***	(0.021)	(0.007)	(0.006)***	(0.028)**	(0.016)**	(0.016)
IS	-0.010	0.001	0.023	-0.018	-0.000	0.014	-0.010	-0.075	0.010
	(0.031)	(0.022)	(0.019)	(0.024)	(0.020)	(0.017)	(0.058)	(0.079)	(0.032)
R-squared	0.194	0.457	0.750	0.213	0.453	0.711	0.438	0.349	0.570
Panel B: residual wages									
XD	-0.006	0.026	0.018	0.006	0.008	0.015	-0.042	-0.015	0.001
	(0.016)	(0.015)*	(0.008)**	(0.016)	(0.010)	(0.004)***	(0.020)**	(0.012)	(0.015)
IS	-0.048	-0.023	0.025	-0.019	-0.002	0.008	-0.046	-0.076	0.034
	(0.031)	(0.016)	(0.018)	(0.022)	(0.011)	(0.015)	(0.052)	(0.047)	(0.029)
R-squared	0.278	0.307	0.548	0.305	0.304	0.470	0.336	0.193	0.331
Obs.	409	409	409	409	409	409	374	374	374

All specifications include state fe, demographic controls and lagged level of dependent variable. Clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In sum, the main result of this subsection – that the export shock has led, in the tradables sector, to an increase in average wages of firms in the lower part of the distribution and a decrease in that of high-paying firms, which is in consonance with the hypothesis that the reduction in between-firm wage dispersion was due to a change in firms' behavior – seems driven by the two subsets of firms: while the effect on the bottom of the distribution seems to be due to firms moving along the average wage distribution, the top part appears to be affected by the firms that stay in the same quintiles in the two years.

A.1.0.2
Skill Composition and Returns in Exporter and Non-Exporter Firms

In tables A.13 and A.14 we investigate if the distinct effects of the export shock on exporters and non-exporters may be related to changes in the skill composition of the workforce employed by these two subsets of firms, as well as in the returns to observable measures of worker skill. To obtain the skill composition of workforce at the micro-region level we regress separately indicators for each educational level (we consider three levels: less than high-school, high-school and college graduates) on micro-region dummies and a vector of demographics that include gender, race and a polynomial on age; the coefficients of the former will give each micro-region's share of the workforce in a given category. The returns on education and experience were obtained by running micro-region level mincerian regressions. As before, we split the sample into exporter and non-exporter firms.

No visible effects of the trade shocks on skill composition of exporter firms were obtained. As for non-exporting firms, there is a positive and statistically significant effect of the export shock on high-school graduates; the magnitude of the effect, however, is modest, comprising only 7% of the initial average level if we compare the 90th and 10th percentiles of shock exposure. There is also a positive effect of the import shock on both high school and college graduates, but these are less precisely estimated, small, and disappear if we consider the balanced panel.

Table A.13: Skill Composition: Exporters vs. Non-Exporters

	(1)	(2)	(3)	(4)
	Exporters		Non-Exporters	
2010-00 diff. in:	High School	Superior	High School	Superior
Panel A: All Firms				
XD	0.006	0.001	0.007	0.000
	(0.009)	(0.002)	(0.003)***	(0.001)
IS	-0.020	0.009	0.017	0.004
	(0.018)	(0.005)*	(0.009)*	(0.002)**
Observations	337	337	408	408
R-squared	0.245	0.231	0.441	0.090
Panel B: Stayers				
XD	0.002	0.001	0.006	-0.000
	(0.009)	(0.002)	(0.003)**	(0.001)
IS	-0.020	0.009	0.008	0.003
	(0.018)	(0.006)	(0.010)	(0.002)
Observations	337	337	408	408
R-squared	0.219	0.207	0.422	0.090

All specifications include state fe, demographic controls and lagged level of dependent variable. Clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Finally, as table A.14 shows, the export shock seems to have increased the college premium and decreased the return to experience in exporting firms, although these effects almost disappear when we look to the balanced panel. Among non-exporters, there is a positive effect of the export shock on the high-school premium, which is precise but of similar magnitude than the effect on the share of high-school graduates.

Table A.14: Skill and Experience Premium: Exporters vs. Non-Exporter

	(1)	(2)	(3)	(4)	(5)	(6)
	Exporters			Non-Exporters		
2010-00 diff. in:	High School	Superior	Experience	High School	Superior	Experience
Panel A: All Firms						
XD	0.007	0.068	-0.004	0.019	-0.001	-0.008
	(0.008)	(0.035)**	(0.002)***	(0.005)***	(0.019)	(0.009)
IS	-0.004	-0.050	-0.001	0.023	0.044	0.114
	(0.014)	(0.044)	(0.004)	(0.014)	(0.055)	(0.111)
Obs.	321	321	321	409	409	409
R-squared	0.258	0.183	0.128	0.355	0.212	0.274
Panel B: Stayers						
XD	-0.002	0.053	-0.007	0.038	0.002	0.000
	(0.012)	(0.040)	(0.004)*	(0.016)**	(0.024)	(0.002)
IS	-0.016	-0.038	-0.005	0.160	0.018	-0.008
	(0.017)	(0.058)	(0.005)	(0.114)	(0.053)	(0.004)*
Obs.	309	309	309	401	401	401
R-squared	0.264	0.139	0.165	0.136	0.256	0.766

All specifications include state fe, demographic controls and lagged level of dependent variable. Clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.2 Robustness

A.2.1 AKM (2019) Standard Errors

In face of the recent proliferation of studies with empirical designs based in shift-share instruments, such as the one adopted in the reduced-form part of this chapter, a number of papers focused on methodological aspects of these strategies, such as identification and inference. In light of this literature, we can broadly point out two distinct hypotheses for identification. At one side, Goldsmith-Pinkham et al. (2020) focuses on exogeneity of the vector of shares, which must be as good as randomly assigned, conditional on the shifters. On the other hand, Borusyak et al. (2018) and Adão et al. (2019, henceforth AKM) show that identification can come from exogeneity of the shifters, which must be as good as randomly assigned (conditional on the shares) and independent across sectors.

AKM also focus on the statistical properties of shift-share estimators and discusses their implications for inference. In particular, they show that since the error term in shift-share regressions may also include shift-share terms, there may be correlation in the errors for units with similar shares, even if they are geographically distant – which implies that geographically-based clustered standard errors may be insufficient to account for the error correlation patterns among units. Putting this in terms of this paper, there may be correlation in errors across micro-regions with similar employment patterns even if these micro-regions are distant from one another, so that the clustering of errors at the meso-region level may be insufficient to account for this correlation structure.

The authors show that the consequence of this may be underestimated confidence intervals, leading to over-rejection of the null hypothesis if this problem is not accounted for. Therefore, they proceed to develop a new procedure for calculating standard errors that corrects for this possible error correlation. They illustrate the procedure by showing that standard errors and confidence intervals in previous research are indeed underestimated – for example, they show that for the seminal paper on the effect of the China shock on employment – Autor et al. (2013) – the corrected confidence intervals are substantially larger, even though the main effects are still statistically significant.

In light of this problem, in this appendix we present the results of all the regressions discussed in Section 1.2 using methodology developed by AKM to obtain the correct standard errors that account for the possible correlation between distant micro-regions with similar employment patterns[2].

As shown in the tables below, the main takeout is analogous to what happened with the results in Autor et al. (2013) reestimated by AKM: although some standard errors are larger, the vast majority of the estimates remain statistically significant at the same levels. As a *caveat*, it should be stressed that since AKM's method assumes only one endogenous shift-share variable and one instrument, separate regressions were run for the export and the import shocks; however, as discussed above and shown in Appendix A.2, results obtained in such a way are very similar to those obtained by including both shocks in the same regression.

[2]We present only the results for the preferred specifications for reasons of space.

Table A.15: Wage Inequality Measure (Tradables)

	Export Shock				Import Shock			
	Coef.	Std. Error	5% Conf. Int. low	5% Conf. Int. up	Coef.	Std. Error	5% Conf. Int. low	5% Conf. Int. up
Panel A: all firms								
d_var (log)	-0.024	0.009***	-0.042	-0.007	-0.007	0.02	-0.046	0.032
d_var (resid)	-0.017	0.006***	-0.030	-0.005	-0.001	0.014	-0.029	0.027
d_p9010 (log)	-0.033	0.017**	-0.066	-0.001	-0.003	0.038	-0.078	0.072
d_p9010 (resid)	-0.028	0.014**	-0.055	0.000	0.003	0.032	-0.060	0.066
d_p9050 (log)	-0.003	0.018	-0.038	0.032	0.008	0.041	-0.072	0.089
d_p9050 (resid)	-0.012	0.012	-0.035	0.011	0.014	0.026	-0.038	0.066
d_p5010 (log)	-0.024	0.008***	-0.040	-0.008	-0.008	0.015	-0.037	0.022
d_p5010 (resid)	-0.013	0.005***	-0.022	-0.004	-0.010	0.011	-0.032	0.012
Panel B: stayer firms								
d_var (log)	-0.033	0.01***	-0.053	-0.013	-0.009	0.021	-0.051	0.033
d_var (resid)	-0.020	0.006***	-0.032	-0.008	-0.001	0.014	-0.028	0.026
d_p9010 (log)	-0.058	0.019***	-0.096	-0.020	-0.015	0.043	-0.099	0.069
d_p9010 (resid)	-0.042	0.015***	-0.071	-0.012	0.011	0.034	-0.055	0.077
d_p9050 (log)	-0.029	0.022	-0.072	0.015	0.022	0.037	-0.051	0.095
d_p9050 (resid)	-0.026	0.014*	-0.053	0.002	0.028	0.026	-0.022	0.079
d_p5010 (log)	-0.024	0.011**	-0.046	-0.003	-0.035	0.02*	-0.075	0.005
d_p5010 (resid)	-0.016	0.006***	-0.027	-0.004	-0.017	0.014	-0.045	0.010
Panel C: other (non-stayer) firms								
d_var (log)	0.005	0.012	-0.019	0.029	-0.003	0.024	-0.050	0.044
d_var (resid)	0.000	0.01	-0.021	0.020	0.005	0.015	-0.025	0.034
d_p9010 (log)	0.013	0.019	-0.024	0.051	0.050	0.043	-0.036	0.135
d_p9010 (resid)	0.003	0.02	-0.036	0.042	0.020	0.034	-0.046	0.087
d_p9050 (log)	0.027	0.009***	0.009	0.046	-0.022	0.037	-0.095	0.051
d_p9050 (resid)	0.014	0.008*	-0.001	0.030	-0.021	0.029	-0.078	0.036
d_p5010 (log)	-0.012	0.015	-0.041	0.017	0.070	0.037*	-0.002	0.142
d_p5010 (resid)	-0.011	0.014	-0.039	0.017	0.041	0.02**	0.003	0.080

Table A.16: Firm Avg Wage Inequality Measure (Tradables)

	Export Shock				Import Shock			
	Coef.	Std. Error	5% Conf. Int. low	5% Conf. Int. up	Coef.	Std. Error	5% Conf. Int. low	5% Conf. Int. up
Panel A: all firms								
d_var (log)	-0.025	0.008***	-0.041	-0.009	-0.011	0.016	-0.042	0.020
d_var (resid)	-0.016	0.005***	-0.026	-0.006	-0.008	0.009	-0.026	0.009
d_p9010 (log)	-0.043	0.02**	-0.082	-0.004	-0.020	0.038	-0.095	0.055
d_p9010 (resid)	-0.033	0.016**	-0.065	-0.001	-0.062	0.043	-0.147	0.023
d_p9050 (log)	-0.026	0.034	-0.092	0.040	0.007	0.072	-0.134	0.147
d_p9050 (resid)	-0.022	0.02	-0.061	0.018	-0.040	0.053	-0.145	0.064
d_p5010 (log)	-0.011	0.02	-0.049	0.028	-0.022	0.037	-0.094	0.050
d_p5010 (resid)	-0.007	0.01	-0.026	0.013	-0.020	0.018	-0.056	0.016
Panel B: stayer firms								
d_var (log)	-0.033	0.009***	-0.051	-0.015	-0.016	0.018	-0.051	0.019
d_var (resid)	-0.019	0.005***	-0.029	-0.009	-0.010	0.009	-0.028	0.008
d_p9010 (log)	-0.101	0.022***	-0.145	-0.057	-0.073	0.053	-0.177	0.032
d_p9010 (resid)	-0.077	0.018***	-0.113	-0.041	-0.074	0.054	-0.180	0.032
d_p9050 (log)	-0.069	0.026***	-0.120	-0.017	-0.013	0.061	-0.133	0.107
d_p9050 (resid)	-0.055	0.017***	-0.088	-0.022	-0.042	0.06	-0.159	0.075
d_p5010 (log)	-0.024	0.016	-0.055	0.006	-0.055	0.026**	-0.106	-0.004
d_p5010 (resid)	-0.014	0.008*	-0.029	0.002	-0.029	0.016*	-0.061	0.003

Table A.17: Firm Fixed Effects Inequality Measure (Tradables)

	Export Shock				Import Shock			
	Coef.	Std. Error	5% Conf. Int. low	5% Conf. Int. up	Coef.	Std. Error	5% Conf. Int. low	5% Conf. Int. up
Panel A: all firms								
d_var (firm fe)	-0.014	0.005***	-0.025	-0.004	-0.017	0.01*	-0.037	0.003
d_p9010 (firm fe)	-0.024	0.013*	-0.050	0.001	-0.056	0.042	-0.137	0.026
d_p9050 (firm fe)	-0.016	0.018	-0.051	0.019	-0.021	0.055	-0.129	0.087
d_p5010 (firm fe)	-0.003	0.017	-0.036	0.029	-0.032	0.025	-0.082	0.017
Panel B: stayer firms								
d_var (firm fe)	-0.019	0.006***	-0.030	-0.007	-0.017	0.01*	-0.037	0.002
d_p9010 (firm fe)	-0.072	0.019***	-0.109	-0.036	-0.070	0.056	-0.180	0.041
d_p9050 (firm fe)	-0.044	0.016***	-0.075	-0.012	-0.005	0.049	-0.102	0.091
d_p5010 (firm fe)	-0.025	0.013**	-0.050	0.000	-0.063	0.025**	-0.111	-0.014

Table A.18: Wage Variance Decomposition

	Export Shock				Import Shock			
	Coef.	Std. Error	5% Conf. Int. low	5% Conf. Int. up	Coef.	Std. Error	5% Conf. Int. low	5% Conf. Int. up
Panel A: all sectors								
between (log wage)	-0.001	0.004	-0.010	0.007	-0.015	0.011	-0.037	0.007
within (log wage)	0.001	0.002	-0.003	0.005	0.013	0.008	-0.003	0.029
share btw (log wage)	-0.001	0.004	-0.008	0.006	-0.023	0.014	-0.051	0.005
between (resid)	-0.002	0.003	-0.007	0.004	-0.011	0.007	-0.025	0.004
within (resid)	0.000	0.001	-0.003	0.002	0.008	0.005	-0.002	0.018
share btw (resid)	-0.003	0.004	-0.010	0.004	-0.028	0.012**	-0.052	-0.004
Panel B: nontradables								
between (log wage)	0.000	0.002	-0.005	0.005	-0.008	0.014	-0.035	0.019
within (log wage)	0.001	0.002	-0.002	0.004	0.016	0.007**	0.002	0.030
share btw (log wage)	-0.002	0.002	-0.007	0.003	-0.017	0.011	-0.039	0.005
between (resid)	-0.001	0.002	-0.004	0.002	-0.010	0.008	-0.025	0.004
within (resid)	0.000	0.001	-0.002	0.002	0.009	0.003***	0.002	0.015
share btw (resid)	-0.002	0.003	-0.007	0.003	-0.024	0.011**	-0.045	-0.003
Panel B: tradables								
between (log wage)	-0.025	0.008***	-0.041	-0.009	-0.011	0.016	-0.042	0.020
within (log wage)	0.002	0.002	-0.003	0.007	0.006	0.008	-0.010	0.021
share btw (log wage)	-0.014	0.005**	-0.024	-0.003	-0.003	0.015	-0.032	0.027
between (resid)	-0.016	0.005***	-0.026	-0.006	-0.008	0.009	-0.026	0.009
within (resid)	0.000	0.003	-0.005	0.005	0.008	0.007	-0.006	0.022
share btw (resid)	-0.015	0.004***	-0.023	-0.008	-0.018	0.013	-0.044	0.007

Table A.19: Avg. Wage Percentiles

	Export Shock				Import Shock			
	Coef.	Std. Error	5% Conf. Int. low	5% Conf. Int. up	Coef.	Std. Error	5% Conf. Int. low	5% Conf. Int. up
Panel A: all sectors								
d_p90 (log)	-0.016	0.014	-0.044	0.013	-0.047	0.044	-0.133	0.040
d_p90 (resid)	0.000	0.014	-0.028	0.028	-0.088	0.047*	-0.180	0.004
d_p50 (log)	0.016	0.007**	0.003	0.029	-0.019	0.024	-0.066	0.027
d_p50 (resid)	0.014	0.007**	0.001	0.028	-0.022	0.028	-0.078	0.033
d_p10 (log)	0.008	0.005	-0.003	0.018	-0.006	0.015	-0.034	0.023
d_p10 (resid)	0.012	0.008	-0.003	0.027	-0.013	0.019	-0.051	0.024
Panel B: tradables								
d_p90 (log)	-0.073	0.024***	-0.120	-0.027	-0.086	0.058	-0.199	0.028
d_p90 (resid)	-0.051	0.023**	-0.097	-0.005	-0.099	0.063	-0.223	0.025
d_p50 (log)	0.000	0.023	-0.045	0.044	-0.065	0.035*	-0.133	0.003
d_p50 (resid)	0.009	0.018	-0.026	0.043	-0.048	0.037	-0.120	0.024
d_p10 (log)	0.028	0.008***	0.012	0.045	-0.006	0.028	-0.061	0.049
d_p10 (resid)	0.025	0.01**	0.006	0.045	-0.007	0.028	-0.062	0.048
Panel B: nontradables								
d_p90 (log)	0.047	0.01***	0.026	0.067	-0.006	0.045	-0.094	0.083
d_p90 (resid)	0.031	0.01***	0.012	0.051	-0.047	0.05	-0.146	0.051
d_p50 (log)	0.018	0.006***	0.007	0.029	-0.032	0.024	-0.080	0.016
d_p50 (resid)	0.015	0.005***	0.005	0.024	-0.024	0.023	-0.070	0.022
d_p10 (log)	0.008	0.006	-0.003	0.019	-0.010	0.013	-0.036	0.015
d_p10 (resid)	0.013	0.005***	0.004	0.022	0.000	0.014	-0.028	0.028

Table A.20: Avg. Wage Percentiles – Firms that Change Avg. Wage Quintile

	Export Shock				Import Shock			
	Coef.	Std. Error	5% Conf. Int. low	up	Coef.	Std. Error	5% Conf. Int. low	up
Panel A: all sectors								
d_p90 (log)	0.053	0.021**	0.011	0.095	-0.131	0.08	-0.288	0.026
d_p90 (resid)	0.038	0.014***	0.011	0.066	-0.086	0.073	-0.230	0.058
d_p50 (log)	0.021	0.005***	0.010	0.032	-0.011	0.02	-0.050	0.027
d_p50 (resid)	0.015	0.005***	0.004	0.026	-0.012	0.03	-0.071	0.047
d_p10 (log)	0.006	0.009	-0.012	0.024	-0.016	0.017	-0.049	0.018
d_p10 (resid)	0.011	0.008	-0.004	0.026	-0.012	0.016	-0.042	0.019
Panel B: tradables								
d_p90 (log)	0.036	0.038	-0.038	0.110	-0.064	0.068	-0.197	0.068
d_p90 (resid)	0.048	0.024**	0.000	0.095	-0.033	0.063	-0.158	0.091
d_p50 (log)	0.040	0.012***	0.017	0.063	-0.029	0.059	-0.144	0.087
d_p50 (resid)	0.032	0.009***	0.014	0.051	-0.020	0.052	-0.122	0.083
d_p10 (log)	0.015	0.011	-0.007	0.037	-0.036	0.032	-0.099	0.027
d_p10 (resid)	0.011	0.012	-0.014	0.035	-0.042	0.038	-0.117	0.032
Panel B: nontradables								
d_p90 (log)	0.035	0.014**	0.007	0.063	-0.063	0.063	-0.186	0.059
d_p90 (resid)	0.021	0.012*	-0.002	0.045	-0.073	0.062	-0.195	0.049
d_p50 (log)	0.015	0.005***	0.005	0.026	-0.017	0.022	-0.060	0.026
d_p50 (resid)	0.016	0.004***	0.008	0.024	-0.005	0.025	-0.054	0.043
d_p10 (log)	0.003	0.008	-0.012	0.018	-0.008	0.017	-0.041	0.025
d_p10 (resid)	0.014	0.006**	0.003	0.025	0.001	0.015	-0.029	0.031

Table A.21: Avg. Wage Percentiles – Firms that Stay in Avg. Wage Quintile

	Export Shock				Import Shock			
	Coef.	Std. Error	5% Conf. Int. low	up	Coef.	Std. Error	5% Conf. Int. low	up
Panel A: all sectors								
d_p90 (log)	-0.023	0.01**	-0.043	-0.003	-0.009	0.017	-0.043	0.024
d_p90 (resid)	-0.008	0.014	-0.034	0.019	-0.048	0.021**	-0.088	-0.007
d_p50 (log)	0.013	0.009	-0.005	0.030	0.001	0.017	-0.033	0.035
d_p50 (resid)	0.025	0.013*	-0.001	0.052	-0.025	0.02	-0.064	0.015
d_p10 (log)	0.022	0.005***	0.012	0.032	0.022	0.02	-0.017	0.061
d_p10 (resid)	0.020	0.007***	0.006	0.033	0.024	0.023	-0.022	0.070
Panel B: tradables								
d_p90 (log)	-0.058	0.02***	-0.097	-0.018	-0.006	0.046	-0.097	0.084
d_p90 (resid)	-0.044	0.019**	-0.082	-0.007	-0.044	0.05	-0.141	0.054
d_p50 (log)	-0.041	0.02**	-0.080	-0.003	-0.069	0.059	-0.185	0.047
d_p50 (resid)	-0.016	0.017	-0.050	0.017	-0.074	0.042*	-0.155	0.008
d_p10 (log)	0.016	0.01	-0.004	0.035	0.008	0.035	-0.060	0.076
d_p10 (resid)	0.002	0.008	-0.014	0.018	0.034	0.03	-0.024	0.092
Panel B: nontradables								
d_p90 (log)	-0.028	0.009***	-0.046	-0.009	-0.018	0.018	-0.054	0.018
d_p90 (resid)	0.005	0.009	-0.014	0.024	-0.019	0.021	-0.060	0.022
d_p50 (log)	0.002	0.005	-0.007	0.011	0.000	0.013	-0.025	0.025
d_p50 (resid)	0.008	0.004*	-0.001	0.017	-0.002	0.012	-0.025	0.020
d_p10 (log)	0.020	0.004***	0.011	0.028	0.013	0.013	-0.013	0.039
d_p10 (resid)	0.015	0.004***	0.008	0.023	0.008	0.017	-0.026	0.042

Table A.22: Employment Around Avg. Wage Percentiles

	Export Shock				Import Shock			
	Coef.	Std. Error	5% Conf. Int. low	up	Coef.	Std. Error	5% Conf. Int. low	up
Panel A: all sectors, employment shares								
d_share_p90 (log)	0.005	0.002**	0.000	0.009	0.008	0.017	-0.024	0.041
d_share_p90 (resid)	-0.003	0.003	-0.009	0.002	0.006	0.011	-0.015	0.028
d_share_p50 (log)	-0.005	0.002***	-0.008	-0.002	-0.003	0.004	-0.010	0.005
d_share_p50 (resid)	-0.002	0.001	-0.004	0.001	-0.001	0.003	-0.008	0.005
d_share_p10 (log)	-0.001	0.002	-0.005	0.002	0.006	0.003**	0.001	0.012
d_share_p10 (resid)	-0.001	0.001	-0.003	0.001	0.002	0.003	-0.003	0.008
Panel A: all sectors, log employment								
d_l_emp_p90 (log)	0.072	0.016***	0.040	0.105	0.113	0.047**	0.021	0.206
d_l_emp_p90 (resid)	0.026	0.021	-0.015	0.066	0.055	0.049	-0.042	0.152
d_l_emp_p50 (log)	-0.193	0.059***	-0.309	-0.076	0.179	0.112	-0.040	0.398
d_l_emp_p50 (resid)	0.029	0.019	-0.008	0.066	0.049	0.048	-0.045	0.144
d_l_emp_p10 (log)	0.023	0.038	-0.052	0.097	0.176	0.066***	0.047	0.306
d_l_emp_p10 (resid)	0.000	0.019	-0.038	0.038	0.043	0.043	-0.041	0.127
Panel B: tradables, employment shares								
d_share_p90 (log)	0.019	0.006***	0.007	0.032	-0.018	0.014	-0.046	0.010
d_share_p90 (resid)	0.007	0.006	-0.005	0.019	-0.033	0.014**	-0.060	-0.006
d_share_p50 (log)	-0.005	0.002*	-0.009	0.000	-0.003	0.009	-0.020	0.014
d_share_p50 (resid)	-0.003	0.002	-0.007	0.001	0.011	0.006*	0.000	0.023
d_share_p10 (log)	0.004	0.002**	0.000	0.007	-0.003	0.005	-0.012	0.006
d_share_p10 (resid)	0.000	0.001	-0.002	0.002	0.002	0.004	-0.005	0.009
Panel B: tradables, log employment								
d_l_emp_p90 (log)	0.134	0.062**	0.012	0.256	-0.083	0.101	-0.281	0.115
d_l_emp_p90 (resid)	0.050	0.058	-0.063	0.163	-0.118	0.099	-0.312	0.077
d_l_emp_p50 (log)	-0.065	0.052	-0.167	0.037	0.183	0.113	-0.039	0.404
d_l_emp_p50 (resid)	-0.045	0.035	-0.112	0.023	0.210	0.117*	-0.019	0.438
d_l_emp_p10 (log)	0.053	0.029*	-0.005	0.110	0.003	0.08	-0.155	0.160
d_l_emp_p10 (resid)	0.009	0.029	-0.048	0.066	0.077	0.082	-0.083	0.236
Panel B: nontradables, employment shares								
d_share_p90 (log)	0.003	0.003	-0.003	0.009	0.004	0.006	-0.009	0.017
d_share_p90 (resid)	-0.006	0.003*	-0.013	0.000	0.004	0.006	-0.008	0.016
d_share_p50 (log)	-0.007	0.001***	-0.010	-0.004	-0.004	0.004	-0.011	0.004
d_share_p50 (resid)	-0.002	0.002	-0.005	0.002	0.005	0.006	-0.007	0.018
d_share_p10 (log)	-0.001	0.002	-0.005	0.003	0.008	0.004*	0.000	0.016
d_share_p10 (resid)	-0.001	0.001	-0.003	0.001	0.003	0.004	-0.005	0.011
Panel B: nontradables, log employment								
d_l_emp_p90 (log)	0.057	0.022***	0.014	0.101	0.067	0.049	-0.029	0.163
d_l_emp_p90 (resid)	0.013	0.025	-0.037	0.062	0.048	0.043	-0.037	0.132
d_l_emp_p50 (log)	-0.219	0.056***	-0.328	-0.109	0.241	0.11**	0.024	0.457
d_l_emp_p50 (resid)	0.022	0.03	-0.037	0.081	0.178	0.061***	0.059	0.298
d_l_emp_p10 (log)	0.032	0.023	-0.014	0.078	0.037	0.04	-0.042	0.115
d_l_emp_p10 (resid)	-0.005	0.015	-0.035	0.024	0.014	0.043	-0.069	0.098

Table A.23: Employment Around Avg. Wage Percentiles – Firms that Change Avg. Wage Quintile

	Export Shock				Import Shock			
	Coef.	Std. Error	5% Conf. Int. low	up	Coef.	Std. Error	5% Conf. Int. low	up
Panel A: all sectors, employment shares								
d_share_p90 (log)	0.006	0.003	-0.001	0.012	-0.019	0.012	-0.043	0.005
d_share_p90 (resid)	-0.003	0.003	-0.009	0.004	-0.001	0.01	-0.020	0.019
d_share_p50 (log)	-0.010	0.002***	-0.013	-0.006	-0.002	0.005	-0.011	0.006
d_share_p50 (resid)	0.001	0.002	-0.003	0.004	0.008	0.008	-0.008	0.024
d_share_p10 (log)	-0.002	0.003	-0.008	0.005	0.006	0.005	-0.004	0.016
d_share_p10 (resid)	-0.002	0.001	-0.005	0.000	0.007	0.006	-0.004	0.018
Panel A: all sectors, log employment								
d_l_emp_p90 (log)	0.052	0.028*	-0.004	0.107	-0.061	0.059	-0.177	0.055
d_l_emp_p90 (resid)	0.012	0.026	-0.040	0.064	0.002	0.085	-0.164	0.168
d_l_emp_p50 (log)	-0.325	0.051***	-0.425	-0.226	0.063	0.123	-0.177	0.304
d_l_emp_p50 (resid)	0.058	0.019***	0.020	0.095	0.069	0.068	-0.065	0.203
d_l_emp_p10 (log)	0.062	0.05	-0.037	0.160	0.173	0.068**	0.039	0.307
d_l_emp_p10 (resid)	0.000	0.023	-0.045	0.046	0.071	0.059	-0.046	0.187
Panel B: tradables, employment shares								
d_share_p90 (log)	-0.006	0.008	-0.023	0.010	0.014	0.016	-0.017	0.046
d_share_p90 (resid)	0.004	0.009	-0.013	0.021	-0.023	0.016	-0.054	0.007
d_share_p50 (log)	-0.014	0.004***	-0.022	-0.007	-0.014	0.014	-0.040	0.013
d_share_p50 (resid)	-0.005	0.003*	-0.011	0.001	0.020	0.011*	-0.001	0.041
d_share_p10 (log)	-0.001	0.004	-0.008	0.007	-0.021	0.019	-0.058	0.015
d_share_p10 (resid)	0.000	0.002	-0.004	0.005	0.006	0.006	-0.005	0.018
Panel B: tradables, log employment								
d_l_emp_p90 (log)	-0.045	0.071	-0.185	0.094	0.169	0.117	-0.061	0.399
d_l_emp_p90 (resid)	0.039	0.054	-0.066	0.145	-0.050	0.117	-0.279	0.179
d_l_emp_p50 (log)	-0.141	0.059**	-0.257	-0.025	-0.169	0.193	-0.547	0.210
d_l_emp_p50 (resid)	-0.081	0.045*	-0.168	0.007	0.133	0.122	-0.105	0.372
d_l_emp_p10 (log)	0.039	0.035	-0.029	0.108	0.047	0.123	-0.195	0.288
d_l_emp_p10 (resid)	0.019	0.038	-0.054	0.093	0.089	0.099	-0.105	0.282
Panel B: nontradables, employment shares								
d_share_p90 (log)	0.006	0.003*	0.000	0.012	-0.018	0.01*	-0.037	0.002
d_share_p90 (resid)	0.001	0.004	-0.007	0.008	0.002	0.009	-0.015	0.019
d_share_p50 (log)	-0.009	0.002***	-0.013	-0.005	-0.002	0.006	-0.013	0.010
d_share_p50 (resid)	-0.002	0.002	-0.005	0.002	0.007	0.008	-0.009	0.024
d_share_p10 (log)	0.000	0.003	-0.006	0.006	0.008	0.005	-0.002	0.018
d_share_p10 (resid)	-0.001	0.001	-0.004	0.001	0.008	0.007	-0.005	0.022
Panel B: nontradables, log employment								
d_l_emp_p90 (log)	0.071	0.021***	0.030	0.113	-0.100	0.046**	-0.191	-0.009
d_l_emp_p90 (resid)	0.039	0.03	-0.019	0.097	0.057	0.07	-0.080	0.194
d_l_emp_p50 (log)	-0.342	0.059***	-0.458	-0.226	0.127	0.159	-0.184	0.437
d_l_emp_p50 (resid)	0.041	0.023*	-0.004	0.086	0.068	0.062	-0.053	0.190
d_l_emp_p10 (log)	0.074	0.046	-0.016	0.164	0.187	0.06***	0.069	0.305
d_l_emp_p10 (resid)	-0.007	0.02	-0.046	0.032	0.072	0.048	-0.022	0.166

Table A.24: Employment Around Avg. Wage Percentiles – Firms that Stay in Avg. Wage Quintile

	Export Shock				Import Shock			
	Coef.	Std. Error	5% Conf. Int. low	5% Conf. Int. up	Coef.	Std. Error	5% Conf. Int. low	5% Conf. Int. up
Panel A: all sectors, employment shares								
d_share_p90 (log)	-0.001	0.004	-0.009	0.006	-0.008	0.013	-0.034	0.018
d_share_p90 (resid)	-0.005	0.005	-0.014	0.004	0.021	0.008***	0.006	0.036
d_share_p50 (log)	0.001	0.003	-0.004	0.007	-0.001	0.008	-0.016	0.015
d_share_p50 (resid)	0.001	0.001	-0.002	0.003	-0.003	0.005	-0.013	0.007
d_share_p10 (log)	0.000	0.001	-0.002	0.002	0.007	0.004*	0.000	0.015
d_share_p10 (resid)	0.000	0.001	-0.002	0.001	-0.004	0.002**	-0.007	0.000
Panel A: all sectors, log employment								
d_l_emp_p90 (log)	0.013	0.024	-0.034	0.060	0.011	0.077	-0.139	0.162
d_l_emp_p90 (resid)	0.002	0.03	-0.058	0.062	0.130	0.044***	0.043	0.216
d_l_emp_p50 (log)	0.037	0.034	-0.030	0.105	0.043	0.071	-0.096	0.183
d_l_emp_p50 (resid)	0.005	0.03	-0.054	0.063	-0.038	0.068	-0.172	0.096
d_l_emp_p10 (log)	-0.032	0.026	-0.082	0.018	0.194	0.058***	0.081	0.308
d_l_emp_p10 (resid)	-0.032	0.017*	-0.065	0.000	-0.105	0.046**	-0.196	-0.015
Panel B: tradables, employment shares								
d_share_p90 (log)	0.004	0.009	-0.013	0.021	-0.006	0.03	-0.064	0.052
d_share_p90 (resid)	0.010	0.007	-0.004	0.025	0.001	0.025	-0.049	0.050
d_share_p50 (log)	-0.004	0.003	-0.009	0.002	0.009	0.011	-0.011	0.030
d_share_p50 (resid)	-0.003	0.003	-0.008	0.003	0.020	0.008**	0.004	0.037
d_share_p10 (log)	-0.002	0.003	-0.007	0.003	0.026	0.01**	0.005	0.046
d_share_p10 (resid)	-0.001	0.002	-0.006	0.004	0.006	0.006	-0.006	0.017
Panel B: tradables, log employment								
d_l_emp_p90 (log)	0.026	0.051	-0.074	0.125	-0.147	0.298	-0.731	0.436
d_l_emp_p90 (resid)	0.120	0.034***	0.053	0.188	-0.031	0.15	-0.326	0.264
d_l_emp_p50 (log)	-0.032	0.045	-0.119	0.056	0.051	0.127	-0.198	0.301
d_l_emp_p50 (resid)	0.005	0.046	-0.084	0.094	0.274	0.109**	0.060	0.487
d_l_emp_p10 (log)	-0.030	0.027	-0.082	0.022	0.082	0.077	-0.069	0.233
d_l_emp_p10 (resid)	0.036	0.039	-0.041	0.113	0.027	0.059	-0.088	0.142
Panel B: nontradables, employment shares								
d_share_p90 (log)	-0.003	0.005	-0.012	0.006	0.011	0.014	-0.017	0.038
d_share_p90 (resid)	-0.005	0.005	-0.015	0.005	0.011	0.011	-0.010	0.033
d_share_p50 (log)	-0.002	0.001*	-0.004	0.000	0.007	0.005	-0.002	0.017
d_share_p50 (resid)	-0.001	0.002	-0.005	0.002	-0.003	0.005	-0.013	0.008
d_share_p10 (log)	-0.001	0.002	-0.004	0.002	0.011	0.007*	-0.002	0.025
d_share_p10 (resid)	-0.001	0.001	-0.002	0.000	-0.004	0.003	-0.009	0.001
Panel B: nontradables, log employment								
d_l_emp_p90 (log)	-0.011	0.028	-0.065	0.044	0.072	0.087	-0.099	0.243
d_l_emp_p90 (resid)	0.006	0.032	-0.057	0.069	0.130	0.065**	0.002	0.258
d_l_emp_p50 (log)	-0.015	0.02	-0.054	0.024	0.141	0.093	-0.043	0.324
d_l_emp_p50 (resid)	-0.007	0.023	-0.052	0.039	-0.001	0.073	-0.145	0.143
d_l_emp_p10 (log)	-0.044	0.032	-0.106	0.019	0.175	0.091*	-0.004	0.354
d_l_emp_p10 (resid)	-0.051	0.013***	-0.076	-0.026	-0.044	0.06	-0.163	0.074

Table A.25: Exporter Wage Premium

	Export Shock				Import Shock			
			5% Conf. Int.				5% Conf. Int.	
Wage Premium of:	Coef.	Std. Error	low	up	Coef.	Std. Error	low	up
exporters	-0.025	0.013**	-0.049	0.000	-0.031	0.024	-0.077	0.016
exporters (stayers)	-0.028	0.014**	-0.055	-0.001	-0.002	0.028	-0.057	0.053
always exporters	-0.037	0.019*	-0.074	0.001	-0.001	0.025	-0.049	0.047
new/former exp.	0.017	0.019	-0.021	0.055	0.036	0.019*	-0.001	0.074
high-paying exp.	-0.047	0.016***	-0.079	-0.015	-0.076	0.03**	-0.134	-0.017
low-paying exp.	0.026	0.012**	0.003	0.049	0.017	0.04	-0.061	0.094

Table A.26: Wage Inequality Measures – Exporters vs. Nonexporters

	Export Shock				Import Shock			
			5% Conf. Int.				5% Conf. Int.	
	Coef.	Std. Error	low	up	Coef.	Std. Error	low	up
Panel A: exporters								
d_var (log)	-0.008	0.012	-0.032	0.016	-0.025	0.035	-0.093	0.044
d_var (resid)	-0.010	0.006	-0.023	0.003	-0.016	0.019	-0.053	0.021
d_p9010 (log)	-0.046	0.034	-0.112	0.021	-0.009	0.093	-0.191	0.174
d_p9010 (resid)	-0.063	0.028**	-0.117	-0.009	-0.069	0.071	-0.208	0.070
d_p9050 (log)	0.052	0.023**	0.007	0.097	-0.047	0.072	-0.187	0.093
d_p9050 (resid)	0.010	0.017	-0.024	0.043	-0.049	0.057	-0.160	0.062
d_p5010 (log)	-0.099	0.022***	-0.143	-0.055	0.047	0.052	-0.055	0.149
d_p5010 (resid)	-0.075	0.016***	-0.107	-0.043	-0.011	0.031	-0.072	0.050
Panel B: Always Exporters								
d_var (log)	0.003	0.012	-0.020	0.026	-0.015	0.031	-0.076	0.046
d_var (resid)	-0.006	0.006	-0.018	0.007	-0.010	0.02	-0.050	0.030
d_p9010 (log)	0.023	0.027	-0.029	0.075	-0.020	0.07	-0.158	0.117
d_p9010 (resid)	-0.013	0.021	-0.054	0.027	-0.044	0.065	-0.171	0.082
d_p9050 (log)	0.099	0.021***	0.058	0.140	-0.098	0.086	-0.266	0.071
d_p9050 (resid)	0.052	0.014***	0.024	0.080	-0.041	0.069	-0.175	0.094
d_p5010 (log)	-0.079	0.022***	-0.122	-0.036	0.078	0.058	-0.035	0.190
d_p5010 (resid)	-0.068	0.014***	-0.096	-0.040	0.007	0.038	-0.068	0.082
Panel C: Non-Exporters								
d_var (log)	-0.002	0.002	-0.007	0.002	0.002	0.006	-0.010	0.014
d_var (resid)	-0.004	0.001***	-0.006	-0.001	0.003	0.004	-0.004	0.010
d_p9010 (log)	0.018	0.009**	0.001	0.036	0.011	0.017	-0.023	0.044
d_p9010 (resid)	0.010	0.007	-0.004	0.024	0.001	0.019	-0.036	0.039
d_p9050 (log)	0.040	0.008***	0.024	0.056	0.027	0.036	-0.044	0.098
d_p9050 (resid)	0.028	0.007***	0.014	0.041	0.009	0.025	-0.039	0.057
d_p5010 (log)	-0.017	0.007**	-0.031	-0.003	-0.018	0.034	-0.086	0.049
d_p5010 (resid)	-0.012	0.007	-0.026	0.002	-0.013	0.026	-0.064	0.038

A.2.2
Main Results – Additional Specifications

Table A.27: Effects of the China Shock on Variance – Tradables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	2010-2000 diff. in Variance											
	observed						residual					
	OLS			IV			OLS			IV		
XD	-0.024	-0.022	-0.022	-0.026	-0.024	-0.024	-0.012	-0.012	-0.012	-0.016	-0.017	-0.017
	(0.012)**	(0.011)*	(0.012)*	(0.011)**	(0.009)***	(0.009)**	(0.007)	(0.007)*	(0.007)*	(0.007)**	(0.006)***	(0.006)***
IS	-0.020	-0.005	-0.005	-0.023	-0.008	-0.008	-0.000	0.002	0.002	-0.003	-0.002	-0.002
	(0.018)	(0.018)	(0.019)	(0.022)	(0.023)	(0.023)	(0.010)	(0.009)	(0.009)	(0.013)	(0.013)	(0.013)
high school		0.134	0.146		0.131	0.225		0.287	0.279		0.281	0.272
		(0.289)	(0.259)		(0.275)	(1.664)		(0.108)***	(0.105)***		(0.101)***	(0.098)***
female		0.240	0.229		0.236			-0.305	-0.308		-0.311	-0.312
		(1.752)	(1.757)		(1.664)			(0.980)	(0.970)		(0.913)	(0.900)
informality		0.197	0.199		0.190	0.191		0.097	0.095		0.084	0.082
		(0.082)**	(0.082)**		(0.075)**	(0.075)**		(0.044)**	(0.044)**		(0.044)*	(0.044)*
lag vardep			-0.006			-0.005			0.015			0.017
			(0.033)			(0.030)			(0.017)			(0.016)
Constant	-0.013	-0.239	-0.233	-0.011	-0.231	-0.225	-0.023	0.042	0.039	-0.020	0.056	0.051
	(0.008)	(0.819)	(0.819)	(0.008)	(0.777)	(0.776)	(0.005)***	(0.466)	(0.460)	(0.005)***	(0.435)	(0.428)
Observations	408	408	404	408	408	404	408	408	404	408	408	404
R-squared	0.272	0.283	0.284	0.272	0.283	0.284	0.212	0.230	0.232	0.210	0.228	0.229

Clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.28: Effects of the China Shock on p90-p10 wage gap – Tradables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	2010-2000 diff. in p90-p10 gap											
	observed						residual					
	OLS			IV			OLS			IV		
XD	-0.031	-0.028	-0.028	-0.035	-0.033	-0.033	-0.016	-0.017	-0.019	-0.023	-0.026	-0.028
	(0.024)	(0.024)	(0.025)	(0.021)	(0.018)*	(0.019)*	(0.015)	(0.015)	(0.015)	(0.013)*	(0.012)**	(0.013)**
IS	-0.024	-0.003	-0.004	-0.024	-0.004	-0.005	0.009	0.015	0.014	0.001	0.003	0.002
	(0.033)	(0.033)	(0.034)	(0.041)	(0.041)	(0.041)	(0.021)	(0.018)	(0.019)	(0.030)	(0.029)	(0.029)
high school		0.616	0.590		0.613	0.584		0.745	0.696		0.730	0.677
		(0.542)	(0.490)		(0.515)	(0.465)		(0.281)***	(0.269)**		(0.270)***	(0.260)***
female		-0.979	-0.964		-0.978	-0.960		-0.523	-0.460		-0.547	-0.478
		(3.813)	(3.770)		(3.622)	(3.574)		(2.324)	(2.266)		(2.188)	(2.127)
informality		0.350	0.351		0.342	0.343		0.251	0.248		0.219	0.215
		(0.161)**	(0.162)**		(0.154)**	(0.154)**		(0.089)***	(0.089)***		(0.093)**	(0.093)**
lag vardep			0.008			0.009			0.031			0.034
			(0.035)			(0.032)			(0.024)			(0.022)
Constant	-0.062	0.158	0.141	-0.060	0.166	0.145	-0.134	-0.090	-0.164	-0.128	-0.054	-0.135
	(0.016)***	(1.789)	(1.751)	(0.015)***	(1.701)	(1.661)	(0.010)***	(1.093)	(1.051)	(0.009)***	(1.030)	(0.988)
Observations	409	409	408	409	409	408	409	409	408	409	409	408
R-squared	0.246	0.255	0.255	0.246	0.254	0.255	0.245	0.271	0.274	0.244	0.269	0.272

Clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.29: Effects of the China Shock on p90-p50 wage gap – Tradables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	2010-2000 diff. in p90-p50 gap											
	observed						residual					
	OLS			IV			OLS			IV		
XD	-0.004	-0.003	-0.003	-0.002	-0.003	-0.003	-0.008	-0.008	-0.008	-0.011	-0.013	-0.013
	(0.025)	(0.024)	(0.024)	(0.021)	(0.019)	(0.018)	(0.015)	(0.014)	(0.014)	(0.013)	(0.011)	(0.011)
IS	0.015	0.027	0.027	0.000	0.008	0.008	0.022	0.026	0.026	0.014	0.014	0.014
	(0.030)	(0.028)	(0.028)	(0.040)	(0.039)	(0.039)	(0.018)	(0.016)	(0.016)	(0.023)	(0.021)	(0.021)
high school		0.749	0.769		0.733	0.754		0.656	0.654		0.644	0.642
		(0.480)	(0.465)		(0.457)	(0.442)*		(0.259)**	(0.260)**		(0.252)**	(0.252)**
female		-0.846	-0.812		-0.893	-0.857		-0.924	-0.928		-0.951	-0.955
		(3.057)	(3.120)		(2.935)	(2.992)		(1.767)	(1.779)		(1.680)	(1.689)
informality		0.300	0.303		0.268	0.271		0.191	0.191		0.164	0.163
		(0.153)*	(0.153)*		(0.144)*	(0.144)*		(0.082)**	(0.084)**		(0.082)**	(0.084)*
lag vardep			-0.012			-0.013			0.003			0.003
			(0.043)			(0.042)			(0.029)			(0.028)
Constant	-0.042	0.128	0.124	-0.041	0.170	0.164	-0.063	0.209	0.208	-0.059	0.241	0.240
	(0.016)**	(1.433)	(1.447)	(0.014)***	(1.378)	(1.390)	(0.010)***	(0.829)	(0.827)	(0.009)***	(0.788)	(0.786)
Observations	409	409	408	409	409	408	409	409	408	409	409	408
R-squared	0.286	0.297	0.298	0.285	0.297	0.297	0.246	0.270	0.270	0.245	0.269	0.269

Clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.30: Effects of the China Shock on p50-p10 wage gap – Tradables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	2010-2000 diff. in p50-p10 gap											
	observed						residual					
	OLS			IV			OLS			IV		
XD	-0.027	-0.025	-0.019	-0.033	-0.030	-0.024	-0.008	-0.009	-0.008	-0.012	-0.013	-0.013
	(0.010)***	(0.009)***	(0.010)*	(0.010)***	(0.009)***	(0.010)**	(0.006)	(0.006)	(0.007)	(0.006)**	(0.006)**	(0.007)*
IS	-0.039	-0.030	-0.024	-0.024	-0.012	-0.009	-0.013	-0.011	-0.011	-0.013	-0.011	-0.011
	(0.014)***	(0.016)*	(0.016)	(0.014)*	(0.016)	(0.016)	(0.010)	(0.011)	(0.011)	(0.013)	(0.014)	(0.014)
high school		-0.132	-0.013		-0.119	-0.003		0.088	0.093		0.086	0.088
		(0.271)	(0.279)		(0.258)	(0.264)		(0.140)	(0.151)		(0.131)	(0.141)
female		-0.133	-0.475		-0.085	-0.431		0.400	0.381		0.404	0.396
		(1.306)	(1.326)		(1.222)	(1.240)		(0.751)	(0.766)		(0.697)	(0.706)
informality		0.049	0.025		0.074	0.046		0.060	0.060		0.055	0.055
		(0.062)	(0.062)		(0.063)	(0.062)		(0.042)	(0.042)		(0.045)	(0.044)
lag vardep			-0.069			-0.069			-0.005			-0.002
			(0.042)			(0.039)*			(0.033)			(0.030)
Constant	-0.020	0.030	0.217	-0.019	-0.004	0.187	-0.071	-0.299	-0.287	-0.069	-0.295	-0.290
	(0.007)***	(0.592)	(0.600)	(0.007)**	(0.552)	(0.560)	(0.004)***	(0.339)	(0.348)	(0.004)***	(0.315)	(0.321)
Observations	409	409	408	409	409	408	409	409	408	409	409	408
R-squared	0.160	0.176	0.200	0.156	0.172	0.197	0.142	0.153	0.153	0.141	0.151	0.151

Clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.31: Effects of the China Shock on Between-Firm Variance – Tradables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	2010-2000 diff. in Between-Firm Variance											
	observed						residual					
	OLS			IV			OLS			IV		
XD	-0.026	-0.025	-0.024	-0.026	-0.025	-0.024	-0.013	-0.013	-0.012	-0.015	-0.016	-0.016
	(0.010)***	(0.010)**	(0.012)**	(0.009)***	(0.008)***	(0.009)***	(0.006)**	(0.006)**	(0.006)*	(0.005)***	(0.005)***	(0.005)***
IS	-0.020	-0.009	-0.009	-0.023	-0.012	-0.012	-0.005	-0.003	-0.003	-0.009	-0.009	-0.009
	(0.017)	(0.018)	(0.018)	(0.019)	(0.019)	(0.019)	(0.008)	(0.008)	(0.008)	(0.010)	(0.009)	(0.009)
high school		0.066	0.110		0.063	0.105		0.168	0.177		0.162	0.168
		(0.244)	(0.213)		(0.234)	(0.205)		(0.082)**	(0.080)**		(0.077)**	(0.075)**
female		0.579	0.576		0.574	0.569		-0.098	-0.108		-0.109	-0.118
		(1.272)	(1.305)		(1.213)	(1.241)		(0.690)	(0.701)		(0.644)	(0.650)
informality		0.145	0.152		0.140	0.146		0.060	0.062		0.047	0.048
		(0.074)*	(0.076)**		(0.070)**	(0.072)**		(0.033)*	(0.035)*		(0.034)	(0.035)
lag vardep			-0.029			-0.028			-0.011			-0.007
			(0.044)			(0.041)			(0.032)			(0.030)
Constant	-0.014	-0.366	-0.366	-0.014	-0.360	-0.358	-0.012	-0.013	-0.009	-0.010	0.001	0.006
	(0.007)**	(0.594)	(0.611)	(0.006)**	(0.567)	(0.581)	(0.004)***	(0.327)	(0.332)	(0.004)***	(0.307)	(0.309)
Observations	406	406	402	406	406	402	406	406	402	406	406	402
R-squared	0.252	0.260	0.261	0.252	0.260	0.261	0.194	0.205	0.206	0.193	0.202	0.203

Clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.32: Effects of the China Shock on Within-Firm Variance – Tradables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	2010-2000 diff. in Within-Firm Variance											
	observed						residual					
	OLS			IV			OLS			IV		
XD	0.003	0.003	0.003	0.001	0.002	0.002	0.001	0.001	0.001	-0.000	-0.001	-0.001
	(0.004)	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
IS	0.001	0.005	0.005	0.002	0.006	0.006	0.007	0.007	0.007	0.008	0.008	0.008
	(0.006)	(0.006)	(0.006)	(0.008)	(0.008)	(0.008)	(0.005)	(0.005)	(0.005)	(0.007)	(0.006)	(0.006)
high school		0.100	0.101		0.100	0.100		0.129	0.128		0.130	0.129
		(0.083)	(0.084)		(0.078)	(0.079)		(0.043)***	(0.043)***		(0.041)***	(0.041)***
female		-0.360	-0.360		-0.358	-0.358		-0.223	-0.220		-0.218	-0.215
		(0.587)	(0.590)		(0.553)	(0.555)		(0.345)	(0.348)		(0.321)	(0.322)
informality		0.057	0.058		0.055	0.056		0.030	0.031		0.031	0.031
		(0.025)**	(0.025)**		(0.023)**	(0.022)**		(0.021)	(0.021)		(0.020)	(0.019)
lag vardep			-0.003			-0.003			0.008			0.008
			(0.016)			(0.015)			(0.004)*			(0.004)**
Constant	-0.000	0.130	0.130	0.001	0.131	0.131	-0.013	0.064	0.061	-0.012	0.062	0.059
	(0.002)	(0.273)	(0.275)	(0.003)	(0.257)	(0.259)	(0.001)***	(0.165)	(0.166)	(0.001)***	(0.153)	(0.154)
Observations	408	408	404	408	408	404	408	408	404	408	408	404
R-squared	0.224	0.240	0.245	0.224	0.239	0.244	0.274	0.297	0.300	0.273	0.296	0.299

Clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.33: Effects of the China Shock on Exporter Wage Premium

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	2010-2000 diff. in Exporter Wage Premium											
	All Firms						Stayers					
	OLS			IV			OLS			IV		
XD	-0.023	-0.026	-0.021	-0.028	-0.033	-0.028	-0.019	-0.022	-0.018	-0.030	-0.035	-0.031
	(0.016)	(0.017)	(0.015)	(0.015)*	(0.014)**	(0.012)**	(0.018)	(0.019)	(0.017)	(0.013)**	(0.013)***	(0.011)***
IS	-0.018	-0.029	-0.019	-0.041	-0.050	-0.040	-0.007	-0.021	-0.013	-0.010	-0.018	-0.010
	(0.019)	(0.020)	(0.020)	(0.023)*	(0.023)**	(0.024)*	(0.017)	(0.019)	(0.019)	(0.023)	(0.024)	(0.025)
high school		-0.112	-0.112		-0.138	-0.138		-0.398	-0.399		-0.418	-0.420
		(0.284)	(0.290)		(0.269)	(0.275)		(0.353)	(0.354)		(0.334)	(0.334)
female		3.506	3.315		3.505	3.325		4.415	4.287		4.460	4.337
		(1.431)**	(1.451)**		(1.350)***	(1.367)**		(1.789)**	(1.798)**		(1.689)***	(1.698)**
informality		-0.038	-0.061		-0.091	-0.113		-0.102	-0.118		-0.114	-0.131
		(0.158)	(0.149)		(0.143)	(0.138)		(0.202)	(0.193)		(0.186)	(0.181)
lag vardep			-0.205			-0.195			-0.157			-0.152
			(0.047)***			(0.046)***			(0.054)***			(0.052)***
Constant	0.485	-1.135	-0.371	0.492	-1.099	-0.370	0.624	-1.362	-0.784	0.632	-1.366	-0.809
	(0.011)***	(0.685)	(0.765)	(0.010)***	(0.638)*	(0.720)	(0.012)***	(0.841)	(0.932)	(0.009)***	(0.791)*	(0.879)
Observations	375	375	375	375	375	375	367	367	367	367	367	367
R-squared	0.131	0.162	0.196	0.127	0.159	0.193	0.111	0.143	0.160	0.109	0.141	0.158

Clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.2.3 Restricted Samples

Table A.34: Exporter Wage Premium – Restricted MMC Samples

	(1)	(2)
	2010-2000 Difference in Exporter Wage Premium	
	Stayers, MMCs with high-paying firms	Stayers, MMCs with low-paying firms
XD	-0.031	-0.038
	(0.011)***	(0.017)**
IS	-0.010	-0.000
	(0.025)	(0.023)
Observations	365	250
R-squared	0.157	0.264

All specifications include state fe, demographic controls and lagged level of dependent variable. High (low) paying firms refer to firms with average residual wages above (below) sector median. Clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.35: Firm Average Wages Inequality Measures – only MMCs with exporting firms

	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Tradables; MMCs with exporters							
	All Firms				Stayer Firms Only			
2010-00 diff. in:	Var.	p90-p10 gap	p90-p50 gap	p50-p10 gap	Var.	p90-p10 gap	p90-p50 gap	p50-p10 gap
Panel A: observed (log) wages								
XD	-0.027	-0.046	-0.032	0.002	-0.031	-0.101	-0.076	-0.019
	(0.011)**	(0.037)	(0.035)	(0.014)	(0.014)**	(0.042)**	(0.037)**	(0.017)
IS	-0.021	-0.033	-0.007	-0.020	-0.021	-0.088	-0.028	-0.058
	(0.021)	(0.049)	(0.069)	(0.025)	(0.016)	(0.045)*	(0.045)	(0.020)***
R-squared	0.433	0.279	0.266	0.358	0.419	0.278	0.272	0.314
Panel B: residual wages								
XD	-0.016	-0.034	-0.021	0.002	-0.018	-0.078	-0.058	-0.006
	(0.006)***	(0.028)	(0.027)	(0.008)	(0.008)**	(0.031)**	(0.024)**	(0.011)
IS	-0.012	-0.071	-0.052	-0.018	-0.012	-0.084	-0.055	-0.028
	(0.010)	(0.046)	(0.044)	(0.015)	(0.008)	(0.047)*	(0.049)	(0.015)*
R-squared	0.331	0.269	0.252	0.335	0.299	0.247	0.229	0.293
Observations	274	274	274	274	259	259	259	259

All specifications include state fe, demographic controls and lagged level of dependent variable. Clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.36: Firm Average Wages Inequality Measures – only MMCs with non-exporting firms

	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Tradables; MMCs with non- exporters							
	All Firms				Stayer Firms Only			
2010-00 diff. in:	Var.	p90-p10 gap	p90-p50 gap	p50-p10 gap	Var.	p90-p10 gap	p90-p50 gap	p50-p10 gap
Panel A: observed (log) wages								
XD	-0.024	-0.042	-0.026	-0.010	-0.032	-0.098	-0.068	-0.023
	(0.009)***	(0.034)	(0.031)	(0.013)	(0.012)***	(0.037)***	(0.033)**	(0.018)
IS	-0.012	-0.015	0.006	-0.017	-0.017	-0.071	-0.016	-0.052
	(0.019)	(0.043)	(0.063)	(0.027)	(0.015)	(0.038)*	(0.044)	(0.020)***
R-squared	0.262	0.190	0.179	0.186	0.261	0.216	0.215	0.209
Panel B: residual wages								
XD	-0.016	-0.030	-0.019	-0.006	-0.019	-0.074	-0.053	-0.012
	(0.005)***	(0.025)	(0.025)	(0.007)	(0.007)***	(0.027)***	(0.022)**	(0.013)
IS	-0.009	-0.057	-0.041	-0.015	-0.010	-0.074	-0.047	-0.026
	(0.009)	(0.041)	(0.042)	(0.016)	(0.007)	(0.043)*	(0.045)	(0.016)
R-squared	0.203	0.194	0.167	0.143	0.182	0.203	0.184	0.175
Observations	401	404	404	404	390	390	390	390

All specifications include state fe, demographic controls and lagged level of dependent variable. Clustered standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.3
Other Candidates for Mechanisms

The reduced-form evidence presented and discussed in the first part of Chapter 1 suggest that the export-demand side of the China shock have contributed to the reduction in wage inequality in the tradables sector, mainly through the between-firms component of wage dispersion, and that this effect has stemmed from changes in firm behavior rather than composition effects. Results also point that changes in the exporter wage premium seems to be the main mechanism driving this compression in the wage dispersion. In this Appendix we present a host of alternative candidates for mechanisms, and show that the evidence does not seem to point to any of these.

First, as table A.37 shows, the export shock doesn't seem to have had an effect on the share of employment on the tradables sector, whether or not we control for demographic characteristics in the first stage (as in the preliminary results of section 1.2). On the contrary, only the import shock seems to have reduced the share of employment in tradables.

Table A.37: Effects of the China Shock on the Share of Employment on the Tradables Sector

	(1)	(2)	(3)	(4)
	Share tradables		Share tradables (controls in first stage)	
XD	0.004	0.002	0.004	0.002
	(0.003)	(0.002)	(0.003)	(0.002)
IS	-0.024	-0.030	-0.024	-0.028
	(0.008)***	(0.009)***	(0.008)***	(0.009)***
state fe	yes	yes	yes	yes
demographic controls	no	yes	no	yes
lagged depvar	no	yes	no	yes
Observations	411	411	412	412
R-squared	0.107	0.148	0.117	0.149

Clustered standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Similarly, the export shock had no effect on the skill composition of the workforce, as shown in table A.38. Again, the import shock seems to have an effect, increasing the share of high-skilled (i.e. high school graduates or higher) workers on the nontradables sector.

Table A.38: Effects of the China Shock on Skill Composition of Workforce

	(1)	(2)	(3)
	2010-2000 diff. in share High Skill		
	All	Nontradables	Tradables
XD	0.005	0.001	0.009
	(0.003)	(0.003)	(0.006)
IS	0.004	0.012	0.016
	(0.006)	(0.006)**	(0.013)
Observations	412	412	412
R-squared	0.336	0.360	0.361

All specifications include state fe, demographic controls and lagged level of dependent variable. Clustered standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

As for the returns on observable characteristics, table A.39 shows that the decline in the experience premium due to the export shock that was found for exporters is also present in the whole of the tradables sectors, and also affects the whole sample. The export shock has also affected the returns for skill, but only through the nontradables sector.

Table A.39: Effects of on Skill and Experience Premia

2010-2000 diff. in:	(1) High School Premium	(2) Experience Premium
Panel A: Full Sample		
XD	0.012	-0.001
	(0.005)**	(0.000)***
IS	0.008	0.000
	(0.014)	(0.001)
Panel B: Nontradable Sectors		
XD	0.010	-0.000
	(0.004)**	(0.000)
IS	0.013	0.001
	(0.012)	(0.001)
Panel C: Tradable Sectors		
XD	0.011	-0.005
	(0.008)	(0.002)**
IS	0.028	0.022
	(0.020)	(0.023)

All specifications include state fe, demographic controls and lagged level of dependent variable. Clustered standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Turning to employment and firm dynamics, we can see from tables A.40 to A.42 that the export side of the China shock had few, if any, effects on the tradables sectors. Table A.40 shows the estimated effects on the difference in entry rates (vis-à-vis the previous year) by quartiles of the wage distribution. There seems to be an increase in entry in low-wage jobs due to the export shock, but no effects on the remaining quartiles, or on exit. In table A.41 , instead of the wage distribution, we focus on quartiles of the firm average wage distribution – in other words, we look at entry and exit in low- and high-paying firms, not jobs. There are no visible effects of the export shock.

Finally, table A.42 shows the effects of the China shock on firm entry and exit by quantiles of the firm average wage distribution. There seems to be no effects of the export shock other than a decline in entry in the top three-quarters of the average wage distribution, but these are too imprecisely estimated to allow any robust conclusions.

Table A.40: Employment Entry and Exit by Wage Quantiles (Tradables)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2010-00 diff. in:	Entry				Exit			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4	Quartile 1	Quartile 2	Quartile 3	Quartile 4
XD	0.007	0.003	-0.001	0.006	0.003	0.005	-0.003	-0.008
	(0.003)**	(0.005)	(0.005)	(0.006)	(0.004)	(0.003)	(0.004)	(0.007)
IS	-0.010	0.033	-0.008	-0.017	-0.016	-0.013	-0.015	-0.030
	(0.008)	(0.021)	(0.010)	(0.013)	(0.015)	(0.007)*	(0.010)	(0.018)*
Observations	408	395	384	369	409	391	377	364
R-squared	0.216	0.132	0.158	0.131	0.350	0.132	0.144	0.135

All specifications include state fe, demographic controls and lagged level of dependent variable. Clustered standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.41: Employment Entry and Exit by Firm Avg. Wage Quantiles (Tradables)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2010-00 diff. in:	Entry				Exit			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4	Quartile 1	Quartile 2	Quartile 3	Quartile 4
XD	-0.002	0.005	-0.001	0.003	0.004	0.003	-0.004	0.001
	(0.005)	(0.007)	(0.010)	(0.008)	(0.006)	(0.003)	(0.008)	(0.006)
IS	0.009	0.017	-0.008	-0.002	0.040	-0.008	-0.039	-0.006
	(0.018)	(0.018)	(0.012)	(0.012)	(0.030)	(0.014)	(0.019)**	(0.009)
Observations	410	396	370	350	405	391	362	345
R-squared	0.270	0.208	0.065	0.164	0.222	0.190	0.107	0.124

All specifications include state fe, demographic controls and lagged level of dependent variable. Clustered standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A.42: Firm Entry and Exit by Firm Avg. Wage Quantiles (Tradables)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2010-00 diff. in:	Entry				Exit			
	Quartile 1	Quartile 2	Quartile 3	Quartile 4	Quartile 1	Quartile 2	Quartile 3	Quartile 4
XD	0.001	-0.007	-0.011	-0.011	0.006	0.002	0.003	0.003
	(0.003)	(0.004)*	(0.009)	(0.006)*	(0.005)	(0.004)	(0.004)	(0.008)
IS	0.005	0.008	-0.013	0.005	0.003	-0.002	-0.004	0.006
	(0.017)	(0.012)	(0.016)	(0.012)	(0.023)	(0.013)	(0.010)	(0.010)
Observations	404	377	343	328	403	373	334	321
R-squared	0.395	0.151	0.072	0.135	0.421	0.084	0.090	0.145

All specifications include state fe, demographic controls and lagged level of dependent variable. Clustered standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A.4
The Model

The structural model consists of a set of sectors populated by a large number J of firms j producing differentiated varieties and supplying two markets, domestic (d) and export (x), under monopolistic competition. In each country there is a continuum of workers that are observationally identical, and which have Constant Elasticity of Substitution (CES) preferences over the sector's varieties, summarized in the real consumption index for a sector Q:

$$Q = \left[\int_{j \in J} q(j)^{\beta} \mathrm{d}j \right]^{1/\beta}$$

where $q(j)$ is the consumption of a given variety j, and $\beta \in (0,1)$ is the parameter that determines the elasticity of substitution across varieties. As HIMR show, the model's predictions for wages and employment across firms within a given sector are independent of general equilibrium effects, so that we can focus on one sector only. Given the CES preferences, the demand equation for a variety j is given by $q(j) = EP^{\frac{\beta}{1-\beta}} p(j)^{-\frac{\beta}{1-\beta}}$, where E is total expenditure and P the ideal price index of the sector, and $p(j)$ is the price of variety j. Defining $A \equiv E^{1-\beta} P^{\beta}$ a sectoral demand shifter – which firms take as given in their decision-making –, the equilibrium revenue of firm j in each market $m \in \{x, m\}$ can be obtained as:

$$r_m(j) = p_m(j) q_m(j) = A_m q_m(j)^{\beta} \tag{A-1}$$

The production technology of each firm is defined as:

$$y = e^{\theta} h^{\gamma} \bar{a} \tag{A-2}$$

where y is firm output, θ is firm productivity, h is the measure of firm employment, $\bar{a}$ is the average ability of the firm's workforce, and $0 < \gamma < 1$; there is, therefore, complementarity between firm and (average) worker productivity[3], which, as noted, will be central in establishing the key result that more productive firms – exporters in particular – will typically pay higher wages.

[3]Helpman et al. (2010) show that a production technology with this feature can be derived by assuming either that human capital exhibits complementarity between each worker and the team she is in, or that production teams are led by a manager who has to allocate a fixed amount of time among the workers under her command.

The exporting activity involves both a fixed cost $e^{\epsilon}F_x$ (with a firm-specific component ϵ) and an iceberg variable cost τ (where, as usual, $\tau > 1$ units of a good must be sent abroad in order to deliver one unit to the foreign consumer). Given these costs, a firm will decide if it will serve the foreign market and, if it does, it will allocate its output between the two markets in order to maximize revenue. We can therefore express total firm revenue, $r(j) = r_d(j) + r_x(j)$, as a function of its total output, $y(j) = y_m(j) + y_x(j)$, the domestic demand shifter A_d, an indicator of its export status (ι, which equals one if the firm exports and zero otherwise), and a *market access* variable ($\Upsilon_x = 1 + \tau^{\frac{-\beta}{1-\beta}} A^{\frac{1}{1-\beta}}$) that summarizes the effect on a firm's revenue of accessing the export market, and depends on *relative external demand* $A \equiv \frac{A_x}{A_d}$ and the variable trade cost:

$$r(j) = [1 + \iota(\Upsilon_x - 1)]^{1-\beta} A_d y(j)^{\beta} \tag{A-3}$$

From (A-3), we can notice the effect of exporting on firm revenue: a firm that does not access the foreign market faces the revenue function $r(j) = A_d y(j)^{\beta}$, which is simply (A-1) for the domestic market. If it becomes an exporter, however, its revenue shifts to $r(j) = \Upsilon_x^{1-\beta} A_d y(j)^{\beta}$; since $\Upsilon_x^{1-\beta}$ is strictly larger than one, it represents the revenue premium earned by the firm that decides to sell in the foreign market – this decision, as will be better detailed ahead, will crucially depend on whether this increase in revenue offsets the fixed cost that the firm must pay in order to engage in exporting activity.

The ability level a of an individual worker is *ex ante* unobservable, both for the worker and for the firms, and is Pareto-distributed, with CDF $G(a) = 1 - a^{-k}$, with $a \geq 1$ and $k > 1$. Labor markets exhibits search and matching frictions as in the Diamond-Mortensen-Pissarides model, in which a firm incurs in a cost equal to bN to match randomly with a measure N of workers; b is endogenously determined by labor market tightness[4]. After matching, even though a firm still cannot identify precisely the ability level of each of the N workers, it can screen them in order to detect and lay off those with ability below a threshold level a_c; to do so, it incurs in a screening cost $e^{-\eta}Ca_c^{\delta}/\delta$, where δ and C are common to all firms but η is firm-specific[5].

Thus, by screening and not hiring workers with productivity below a stipulated level, the firm is able to increase the average productivity of its workforce, but at a cost that is increasing in the threshold value a_c. Conse-

[4]As in HIMR, since the workers' decision of which sector she will search for employment in is inconsequential for the econometric model and empirical application, we do not explicitly model it here, and refer the reader to Helpman et al. (2010).

[5]We also assume $\delta > k$ in order to guarantee a positive size-wage premium in equilibrium.

quently, given the complementarity between firm productivity and workers' average ability in (A-2), more productive firms will have more incentive to be more rigid in their screening policies, and therefore will tend to have workforce with higher $\bar{a}$ (the firm-specific components of screening cost will preclude the existence of perfect assortative matching, which would be at odds with the actual data). A more stringent screening policy will also come at the cost of reducing the measure of workers actually hired: given the Pareto distribution of worker ability, a firm that matches with n workers and chooses threshold a_c will hire $h = na_c^{-k}$ workers with average ability $\bar{a} = ka_c/(k-1)$ (this level is the only information known to firms and workers about the ability profile of the firm's workforce). Substituting these expressions for $\bar{a}$ and h into (A-2), we can rewrite the production function as:

$$y = \frac{k}{k-1} e^{\theta} n^{\gamma} a_c^{1-\gamma k} \tag{A-4}$$

We can then substitute this into (A-3) in order to express firm revenue as a function solely of parameters, the (exogenous) market access variable and the choice variables of the firm:

$$r(n, a_c, \iota) = [1 + \iota(\Upsilon_x - 1)]^{1-\beta} A_d \kappa_y e^{\theta\beta} n^{\gamma\beta} a_c^{\beta(1-\gamma k)} \tag{A-5}$$

where $\kappa_y \equiv [k/(k-1)]^{\beta}$

Wages are set through a multilateral bargaining process modeled as in Stole and Zwiebel (1996), which (as shown by Helpman et al. (2010)) results in the firm receiving a fraction of revenue equal to $r(j)/(1+\beta\gamma)$, while each worker receives a wage equal to $w = \frac{\beta\gamma}{1+\beta\gamma}\frac{r(j)}{h(j)}$. Two crucial aspects of this wage equation should be stressed. First, wages are the same to all workers in the same firm, since the average ability level $\bar{a}$ is the only information on which the bargaining process is conducted. And second, given that wages are a constant fraction of firm revenue, more productive firms will tend to pay higher wages, and exporting firms will on average pay higher wages than a firm, even if we condition on productivity and size – in other words, part of the revenue premium earned by exporter firms, embodied in the market access variable Υ_x, is transferred to the workers in the bargaining process, and becomes the *exporter wage premium*. It should be noted, however, that neither of these relationships – which will manifest themselves on data as positive correlations between productivity, size, revenue, and wages, as well as higher average revenue and wages for exporters conditional on size – are perfect, due to the existence of firm-specific components of both screening and fixed export costs.

The firm problem is to choose the determinants of employment size – the measure of workers matched n and the screening threshold value a_c – and export status, taking as given the result of the bargaining process:

$$\pi(\theta) = \max_{n,a_c,\iota} \left\{ \frac{\beta\gamma}{1+\beta\gamma} r(n, a_c, \iota) - bn - \frac{Ce^{-\eta}}{\delta}(a_c)^{\delta} - \iota F_x e^{\epsilon} \right\} \tag{A-6}$$

The solution to (A-6) implies, as shown in Appendix A.5, the following equilibrium conditions for firm revenue, employment and wages as functions of firm productivity θ, firm idiosyncratic screening cost component η, firm export status ι and the market access variable Υ_x:

$$\begin{aligned} r &= \kappa_r[1+\iota(\Upsilon_x - 1)]^{\xi_1}(e^{\theta})^{\xi_2}(e^{\eta})^{\xi_2\xi_3} && \text{(A-7)} \\ h &= \kappa_h[1+\iota(\Upsilon_x - 1)]^{\xi_1\xi_4}(e^{\theta})^{\xi_2\xi_4}(e^{\eta})^{\xi_5} && \text{(A-8)} \\ w &= \kappa_w[1+\iota(\Upsilon_x - 1)]^{\xi_1\xi_6}(e^{\theta})^{\xi_2\xi_6}(e^{\eta})^{\xi_6\xi_7} && \text{(A-9)} \end{aligned}$$

as well as the following condition for determining export status:

$$\iota = 1 \iff \kappa_\pi \left(\Upsilon_x^{\xi_1} - 1\right)(e^{\theta})^{\xi_2}(e^{\eta})^{\xi_2\xi_3} \geq F_x e^{\epsilon} \tag{A-10}$$

where ξ_1–ξ_7 are combinations of parameters $\{\beta, \gamma, \delta, k\}$, and κ_i, $i = r, h, w, \pi$, are combinations of parameters and aggregate variables, defined in Appendix A.5.

The four equilibrium conditions illustrate clearly a key feature of the model, which is the two-sided nature of the relationship between firm characteristics and the decision to export. There is a *selection effect*: high productivity firms, which tend to be larger and pay higher wages, are also more likely to become an exporter, since its revenue premium is more likely to be large enough to cover the fixed cost. But there is also the *market access effect*, in which accessing the export market boosts firm revenue, thus increasing firm employment and wages – the result is that exporter firms will tend to have higher average wages even after controlling for other firm characteristics such as productivity and size. The latter effect is at the root of the exporter wage premium as understood in the last section; thus, in the next subsection we will use the structure of the model to derive an estimable econometric model that is able to identify these two mechanisms, and in the following one we use the estimated parameters to perform a counterfactual exercise designed to examine how the rise in China could have affected the relative external demand A across sectors, and its effects on the exporter wage premium and on wage inequality.

A.5 Additional Derivations

The first order conditions of the firm's problem (A-6) for n and a_c are, respectively (denoting optimal values with asterisks):

$$n^* = \frac{\beta\gamma}{1+\beta\gamma}\Upsilon^{1-\beta}A_d b^{-1}Y^{*\beta}$$

and

$$a_c^{*\delta} = \frac{\beta(1-\gamma k)}{1+\beta\gamma}\Upsilon^{1-\beta}A_d\frac{1}{e^{-\eta}C}Y^{*\beta}$$

where we denote $\Upsilon = 1+\iota(\Upsilon_x - 1)$ for convenience.

Using these FOCs and the expression for Y in (A-4), we can obtain expressions for n^* and a_c^* in terms of the two structural shocks, the market access variables, and other aggregate variables and parameters:

$$n^* = \left(\frac{\beta\gamma\kappa_y}{1+\beta\gamma}\right)^{\frac{1}{\Gamma}}\left(\frac{1-\gamma k}{\gamma C}\right)^{\frac{\beta(1-\gamma k)}{\delta\Gamma}} b^{-\frac{\beta\gamma+\Gamma}{\Gamma}}A_d^{\frac{\delta-\beta}{\Gamma}}\Upsilon^{\frac{1-\beta}{\Gamma}}(e^\theta)^{\frac{\beta}{\Gamma}}(e^\eta)^{\frac{\beta(1-\gamma k)}{\delta\Gamma}}$$

and

$$a_c^* = \left(\frac{\beta\gamma\kappa_y}{1+\beta\gamma}\right)^{\frac{1}{\delta\Gamma}}\left(\frac{1-\gamma k}{\gamma C}\right)^{\frac{1-\beta\gamma}{\delta\Gamma}} b^{-\frac{\beta\gamma}{\delta\Gamma}}A_d^{\frac{\delta-\beta}{\delta\Gamma}}\Upsilon^{\frac{1-\beta}{\delta\Gamma}}(e^\theta)^{\frac{\beta}{\delta\Gamma}}(e^\eta)^{\frac{1-\beta\gamma}{\delta\Gamma}}$$

where $\Gamma = 1-\beta\gamma-\frac{\beta(1-\gamma k)}{\delta}$.

Substituting these and (A-4) into the expression for firm revenue (A-3) and rearranging we will obtain:

$$r = \kappa_r\Upsilon^{\frac{1-\beta}{\Gamma}}(e^\theta)^{\frac{\beta}{\Gamma}}(e^\eta)^{\frac{\beta(1-\gamma k)}{\delta\Gamma}}$$

where $\kappa_r = \left(\frac{\beta\gamma\kappa_y}{1+\beta\gamma}\right)^{\frac{1}{\Gamma}}\left(\frac{1-\gamma k}{\gamma C}\right)^{\frac{\beta(1-\gamma k)}{\delta\Gamma}}$.

Similarly, substituting the above expressions for n^* and a_c^* into the measure of workers hired, $h = na_c^{-k}$ and rearranging we'll obtain:

$$h = \kappa_h\Upsilon^{\frac{(1-\beta)(1-k/\delta)}{\Gamma}}(e^\theta)^{\frac{\beta(1-k/\delta)}{\Gamma}}(e^\eta)^{-\frac{k-\beta}{\delta\Gamma}}$$

where $k_h = \left(\frac{k}{\delta}\right)^{\frac{1}{\Gamma}} \left(\frac{1-\gamma k}{\gamma C}\right)^{\frac{k(1-\beta\gamma)}{\beta(1-\gamma k)}} b^{\frac{\beta\gamma+\Gamma}{\beta\gamma k}} A_d^{\frac{\delta}{k}}$.

Now substituting the resulting expressions for r and h into the expression for wages results in:

$$w = \kappa_w \Upsilon^{\frac{k(1-\beta)}{\delta\Gamma}} \left(e^{\theta}\right)^{\frac{\beta k}{\delta\Gamma}} \left(e^{\eta}\right)^{\frac{k(1-\beta\gamma)}{\delta\Gamma}}$$

where $k_w = \frac{\beta\gamma}{1+\beta\gamma}\frac{\kappa_r}{\kappa_h}$.

From the first order conditions we can also write the optimal profit of a firm as:

$$\Pi^* = \frac{\Gamma}{1+\beta\gamma} r^* - \iota F_x e^{\epsilon}$$

which implies that export status will be determined by the following condition:

$$\iota = 1 \quad \Leftrightarrow \quad \kappa_\pi \left(\Upsilon_x^{\frac{1-\beta}{\Gamma}} - 1\right) \left(e^{\theta}\right)^{\frac{\beta}{\Gamma}} \left(e^{\eta}\right)^{\frac{\beta(1-\gamma k)}{\delta\Gamma}} \geq F_x e^{\epsilon}$$

where $\kappa_p i = \frac{\Gamma\kappa_r}{1+\beta\gamma}$.

Finally, to obtain (A-7)-(A-10) as expressed in the main text, we simply define the composite parameters $\xi_1 = \frac{1-\beta}{\Gamma}$; $\xi_2 = \frac{\beta}{\Gamma}$; $\xi_3 = \frac{1-\gamma k}{\delta}$; $\xi_4 = 1 - k/\delta$; $\xi_5 = -\frac{k-\beta}{\delta\Gamma}$; $\xi_6 = \frac{k}{\delta}$; and $\xi_7 = \frac{1-\beta\gamma}{\delta}$.

A.6
Derivation of the Econometric Model

To obtain the first equation of the econometric model, (1-9), we take logs of equation A-8:

$$\log(h) = \log(\kappa_h) + \xi_4 \log \Upsilon_x^{\xi_1} \iota + \xi_2\xi_4\theta - \xi_5\eta$$

and then define the combined parameters: $\alpha_h = \log(\kappa_h)$; $\mu_h = \xi_4 \log \Upsilon_x^{\xi_1} = \frac{\delta-k}{\delta} \log \Upsilon_x^{\xi_1}$; and $u = \xi_2\xi_4\theta - \xi_5\eta$.

To obtain (1-10), begin similarly by taking logs of (A-9):

$$\log(w) = \log(\kappa_w) + \xi_6 \log \Upsilon_x^{\xi_1} \iota + \xi_2\xi_6\theta - \xi_6\xi_7\eta$$

and define $\alpha_w = \log(\kappa_w)$; $\mu_w = \xi_6 \log \Upsilon_x^{\xi_1} = \frac{k}{\delta} \log \Upsilon_x^{\xi_1}$; and $\omega = \xi_2\xi_6\theta - \xi_6\xi_7\eta$; but given that joint normality of (θ, η) implies joint normality of (u, ω), we can further define $\omega = \zeta u + v$, where $\zeta = \frac{cov(\omega,u)}{var(u)}$ and $\zeta u = \mathbb{E}[\omega|u]$, obtaining (1-10). Note that the residual v is, by definition, orthogonal to u and jointly normal with (u, ω). HIMR provide a closed-form expression for the projection coefficient ζ.

To obtainthe new selection equation, take logs of (A-10):

$$\log(\kappa_\pi) + \log\left(\Upsilon_x^{\xi_1} - 1\right) + \xi_2\theta + \xi_2\xi_3\eta \geq \log(F_x) + \epsilon$$

which, given the definitions of u and v above, and of $\xi_1 - \xi_7$ in the previous section, can be rewritten as:

$$u + \omega - \epsilon \geq \log(F_x) - \log(\kappa_\pi) - \log\left(\Upsilon_x^{\xi_1} - 1\right)$$

As HIMR show, we can combine the three shocks into an overall shock:

$$z = \frac{u + \omega - \epsilon}{\sqrt{var(u + \omega - \epsilon)}} = \frac{u + \omega - \epsilon}{\sigma}$$

Defining, similarly as before, $\alpha_\pi = \log(\kappa_\pi)$, the selection equation becomes:

$$z \geq \frac{1}{\sigma}\left(\log(F_x) - \log(\kappa_\pi) - \log\left(\Upsilon_x^{\xi_1} - 1\right)\right) \equiv f$$

where the right-hand term in the inequality is the combined parameter f in (1-14).

In the remainder of this section we show how HIMR obtain the likelihood function for the econometric model. We divide the probability each observation into two cases depending on whether the observation describes an exporter or a non-exporter:

$$\mathbb{P}[x_j|\Theta] = \begin{cases} \mathbb{P}[h, w, \iota = 0] = \mathbb{P}[h, w, z < f], & \text{if non-exporter} \\ \mathbb{P}[h, w, \iota = 1] = \mathbb{P}[h, w, z \geq f], & \text{if exporter} \end{cases}$$

Given the selection equation, the two cases become:

$$\mathbb{P}[u = h - \alpha_h, v = (w - \alpha_w) - \zeta(h - \alpha_h), z \geq f] = \int_{\bar{z} < f} \mathbb{P}[u = h - \alpha_h, v = (w - \alpha_w) - \zeta(h - \alpha_h), z = \bar{z}]$$

for non-exporters, and:

$$\mathbb{P}[u = h - \alpha_h - \mu_h, v = (w - \alpha_w - \mu_w) - \zeta(h - \alpha_h - \mu_h), z < f] = \\ \int_{\bar{z} \geq f} \mathbb{P}[u = h - \alpha_h - \mu_h, v = (w - \alpha_w - \mu_w) - \zeta(h - \alpha_h - \mu_h), z = \bar{z}]$$

Given hypothesis of normality of the shocks, we can obtain the probabilities of $(u, v, z < f)$ and $(u, v, z \geq f)$ by integrating over the relevant ranges of z the joint density $\mathbb{P}[u, v, z]$, which is given by:

$$\begin{aligned}\mathbb{P}[u,v,z] &= \mathbb{P}[z|u,v]\mathbb{P}[u,v]\\ &= \frac{1}{\sigma_u}\phi\left(\frac{u}{\sigma_u}\right)\cdot\frac{1}{\sigma_v}\phi\left(\frac{v}{\sigma_v}\right)\cdot\frac{1}{\sqrt{1-\rho_u^2-\rho_v^2}}\phi\left(\frac{z-\rho_u\frac{u}{\sigma_u}-\rho_v\frac{v}{\sigma_v}}{\sqrt{1-\rho_u^2-\rho_v^2}}\right)\end{aligned}$$

(where ϕ denotes the standard normal PDF); doing so we'll obtain (denoting by Φ the standard normal CDF):

$$\mathbb{P}[u,v,z] = \frac{1}{\sigma_u}\phi\left(\frac{u}{\sigma_u}\right)\cdot\frac{1}{\sigma_v}\phi\left(\frac{v}{\sigma_v}\right)\cdot\Phi\left(\frac{f-\rho_u\frac{u}{\sigma_u}-\rho_v\frac{v}{\sigma_v}}{\sqrt{1-\rho_u^2-\rho_v^2}}\right)$$

and

$$\mathbb{P}[u,v,z] = \frac{1}{\sigma_u}\phi\left(\frac{u}{\sigma_u}\right)\cdot\frac{1}{\sigma_v}\phi\left(\frac{v}{\sigma_v}\right)\cdot\left(1-\Phi\left(\frac{f-\rho_u\frac{u}{\sigma_u}-\rho_v\frac{v}{\sigma_v}}{\sqrt{1-\rho_u^2-\rho_v^2}}\right)\right)$$

respectively for non-exporters and exporters.

Combining the two expressions and substituting in the parameters for u and v in each case will result in the likelihood function in subsection 1.3.3.

A.7 Model Fit

In order to examine the fit of the model, we simulated an artificial dataset using the estimated parameters, aggregating sectors according to their relative size in the actual data. We then calculated a set of firm- and worker-level moments for this dataset and actual data; tables A.43 to A.46 display the results.

Table A.43: Firm Moments: Data vs. Model

	All Firms		Non-Exporters		Exporters	
	Data	Model	Data	Model	Data	Model
Mean employment	1.74	1.74	1.62	1.62	4.00	4.00
Mean wages	-0.36	-0.36	-0.38	-0.38	0.04	0.03
St. dev. employment	1.36	1.36	1.23	1.25	1.65	1.30
St. dev. wages	0.40	0.40	0.39	0.39	0.46	0.43
Corr. empl. & wages	0.30	0.30	0.23	0.24	0.30	0.24
Fraction of exporters	0.05	0.05				

In table A.43 we present the average and standard deviation of firm-level employment and wages, as well as the correlation between employment and wages, for all firms and separately for exporters and non-exporters. The model fits very well the firm-level moments for all firms and for non-exporters, although it underestimates the dispersion of employment and its correlation with wages; the quality of the model fit is very similar to the one obtained in HIMR.

Table A.44: Workers' Wage Dispersion: Data vs. Model

	Data	Model		Data	Model
Std. Deviation:			Percentile Ratios:		
All Firms	0.48	0.47	90-10 ratio	3.53	3.32
Non-Exporters	0.40	0.40	90-50 ratio	2.06	1.89
Exporters	0.45	0.45	50-10 ratio	1.72	1.75

As for the workers' level dispersion of wages, displayed in table A.44, the model seems to fit well the standard deviation, even though it performs differently in different portions of the wage distribution, underestimating the 90-10 and 90-50 percentile ratios and slightly overestimating the 50-10 gap. Notice, however, that although the model fit is not perfect for the 2000 levels these wage ratios between percentiles, the model emulates fairly well their changes across time, as reported in table A.45.

Table A.45: Change in Workers' Wage Dispersion: Data vs. Model

	Data			Model		
	2000	2010	Change	2000	2010	Change
Std. Deviation:	0.48	0.40	-0.179	0.47	0.39	-0.181
90-10 ratio	3.53	2.69	-0.240	3.32	2.68	-0.191
90-50 ratio	2.06	1.78	-0.134	1.89	1.71	-0.097
50-10 ratio	1.72	1.51	-0.123	1.75	1.57	-0.105

Finally, table A.46 presents the results of cross-sectional regressions of firm-level wages on firm employment and export status, in order to show that the model is capable of capturing the relationship between these variables that is present in the data. Predictably, both coefficients are positive (reflecting the fact that larger firms pay higher wages, and exporters pay higher wages conditional on their size); the small R-squared coefficient shows, however, that both in the actual and simulated data there is still much variation in wages after controlling for these two factors.

Table A.46: Size and Exporter Premium: Data vs. Model

	Data	Model
Size premium	0.07	0.07
Exporter premium	0.25	0.24
R-squared	0.11	0.10

In summary, although not perfect in some cases, these results show that the model is able to fit fairly well a set of moments of the wage distribution that were not targeted in the estimation, including less trivial ones such as the gaps between wage percentiles. In the next subsection, we use the estimated parameters for the base year in order to perform a counterfactual exercise that aims to capture the interrelationship between external demand, the exporter wage premium, and wage inequality.

A.8 Model Estimates by Sector

Table A.47: Model Estimates by Sector (2000)

Sector	Parameters				
	μ_h	μ_w	ρ_u	ρ_v	f
1	1.923***	0.077***	0.043***	0.178***	1.811***
2	1.833***	0.207***	-0.00***	0.159***	1.643***
3	3.038***	0.222***	0.047***	0.224***	1.952***
4	2.377***	0.101***	0.024***	0.184***	1.792***
5	2.285***	0.189***	0.006	-0.02***	1.740***
6	2.066***	0.236***	0.054	0.427***	1.093***
7	1.598***	0.129***	0.194***	0.313***	1.367***
8	2.432***	0.155***	-0.09	0.376***	1.925***
9	2.414***	0.253***	0.070***	0.205***	1.707***
10	1.777***	0.157***	0.103***	0.279***	1.069***
11	1.861***	0.165***	0.126***	0.295***	1.084***
12	2.633***	0.290***	0.068***	0.313***	1.183***
13	1.997***	0.140***	0.005	0.168***	1.647***

Table A.48: Model Estimates by Sector (2010)

Sector	Parameters				
	μ_h	μ_w	ρ_u	ρ_v	f
1	2.299***	0.143***	0.043***	0.140***	2.008***
2	2.079***	0.247***	0.018	0.238***	1.687***
3	2.865***	0.168***	0.059***	0.217***	1.891***
4	1.963***	0.081***	0.051***	0.203***	1.959***
5	2.438***	0.167***	0.003	0.075***	1.977***
6	1.834***	0.173***	0.150***	0.360***	1.031***
7	1.586***	0.104***	0.193***	0.295***	1.426***
8	1.919***	0.110***	0.063***	0.381***	2.020***
9	2.296***	0.202***	0.108***	0.212***	1.853***
10	1.500***	0.107***	0.147***	0.279***	1.079***
11	1.734***	0.132***	0.110***	0.283***	1.016***
12	2.669***	0.247***	0.084***	0.270***	1.180***
13	1.887***	0.129***	0.014	0.095***	1.806***

B
Appendix to Chapter 2

B.1
Model Overview

B.1.1
The Model

The model considers J sectors (indexed by j or k) and N countries (indexed by n or i). Time is discrete and, each period, households in a given country (which have perfect foresight) choose optimally the sector in which they will work[1], taking into account the cost they incur in changing sectors (which is fixed in time) and a time-variable idiosyncratic preference component for sectors, as in ACM.

Each sector features a competitive labor market, and a *continuum* of firms producing intermediate goods in a perfectly competitive environment, by combining labor, structures (which is a input analogous to physical capital) and inputs from all sectors in a Cobb-Douglas production function with stochastic productivity, which follows (as in EK) a Fréchet distribution with dispersion parameter θ^j (which is the same for all firms in a given sector). In each country, all varieties of a given sector – acquired from wherever it can be supplied with the lowest cost (including the burden of bilateral trade costs) – are combined in a sectoral aggregate good, which is used both as final consumption and as input in the production of varieties in all sectors[2].

Households

Households are *forward looking* and discount future consumption at rate $\beta \geq 0$. Each household is endowed with only one type of labor, U or S, and cannot change it (that is, we abstract from endogenous human capital

[1]The model abstracts from international migration.

[2]To grasp the difference between varieties and local aggregates, consider as example one sector from the empirical application below, such as "textiles, footwork and apparel". In this case, varieties may include textiles (such as fibers), apparel items, leather products, or shoes, for example. Each purchased "unit" of an aggregate good from this sector is a bundle of such varieties, which may be used as final consumption or as intermediate input to produce other varieties from this or other sectors.

decisions); their consumption preferences are defined over a Cobb-Douglas aggregate of local final goods[3], which is the same for the two labor types, and is given by:

$$C_t^j = \prod_{k=1}^{J} (c_t^{j,k})^{\alpha^k} \tag{B-1}$$

where $c_t^{j,k}$ is the consumption of k-sector goods by a family employed in sector j in period t, and $\sum_{k=1}^{J} \alpha^k = 1$.

At each period t, a household may be employed in one of the J sectors – supplying inelastically one unit of it's kind labor $l \in \{U, S\}$ in return for the competitive wage $w_{l,t}^j$, and therefore with its consumption level given by sectoral real wages $C_t^j = w_{l,t}^j / P_t$, where $P_t = \prod_{k=1}^{J} (P_t^k / \alpha^k)^{alpha^k}$ is the ideal price level implied by the aggregator C_t^j – or unemployed, in which case its consumption will be equal to $b > 0$, a parameter that may be interpreted either as unemployment insurance or as domestic subsistence production[4] (in order to simplify the notation, unemployment is denoted as the sector 0.

Households start each period in a given sector (including the sector 0 that denotes unemployment), earn the income associated to this sector, observe wages and prices in each sector, and discover the value of their idiosyncratic sectoral preference shock, ϵ_t^j – which distribution is Type I Extreme Value with zero average. Given these data, they decide whether or not to change their sector in the next period; in order to move from sector j to sector k, a cost equal to $\tau^{j,k}$, which is constant in time and measured in utility units.

The l-type household's dynamic problem is, therefore, to choose the sequence of sectors $\{j\}_{t=0}^{\infty}$ which maximizes the discounted value of lifetime utility, and may be formalized as:

$$v_{l,t}^j = U(C_{l,t}^j) + \max_k \{\beta E[v_{l,t+1}^k] - \tau^{j,k} + \nu_l \epsilon_t^k\}$$
$$\text{s.t.} \quad C_t^j \equiv \begin{cases} b, & \text{if } j = 0 \\ w_t^j / P_t, & \text{otherwise} \end{cases}$$

where nu_l is a parameter that determines the variance of the idiosyncratic shocks. Denoting $V_{l,t}^j \equiv E[v_{l,t}^k]$ the expected utility of a l-type representative

[3]Note that even though households consume only local final goods, these are produced using inputs sourced from all countries; thus, international trade is key in this model.

[4]As it will be detailed ahead, data constraints will force us to lump unemployment and informality in the empirical application, in which case b may also be interpreted as informal labor income

household employed in sector j, the properties of the distribution of ϵ_t^j allow us to rewrite[5] the value of being employed in a given sector at a given period as the sum of the current utility obtained in that sector plus the option value of switching sectors in the next period:

$$V_{l,t}^{j} = U(C_j^j) + \nu_l log \left(\sum_{k=0}^{J} \exp(\beta V_{l,t+1}^{k} - \tau^{j,k})^{1/\nu_l} \right) \tag{B-2}$$

Consider the fraction of l-type households that decide to move from sector j to sector k, $\mu_{l,t}^{j,k}$[6]. Since households choose their sector optimally, they will move to sector k if the continuation value (net of costs) in k is larger than that of every other sector (including that of their current sector). Therefore, $\mu_t^{j,k}$ can be interpreted as the probability that the expected utility in k is the largest among all sectors; using the properties of the Type I Extreme Value distribution allows us to obtain[7]:

$$\mu_{l,t}^{j,k} = \frac{\exp(\beta V_{l,t+1}^{k} - \tau^{j,k})^{1/\nu_l}}{\sum\limits_{h=0}^{J} \exp(\beta V_{l,t+1}^{h} - \tau^{j,h})^{1/\nu_l}} \tag{B-3}$$

That is, *ceteris paribus*, sectors with higher future expected utility (net of mobility costs) will attract more workers, with a mobility elasticity given by $1/\nu_l$. Notice, moreover, that equation (B-3) allows us to reconstruct the distribution of the country's labor force of each type across sectors over time:

$$U_{t+1}^{j} = \sum_{k=0}^{J} \mu_{u,t}^{j,k} U_t^k \quad \text{and} \quad S_{t+1}^{j} = \sum_{k=0}^{J} \mu_{s,t}^{j,k} S_t^k \tag{B-4}$$

Defining the aggregate labor stock in a given period as $L_t = U_t + S_t$, we can define a similar relationship for aggregate labor:

$$L_{t+1}^{j} = \sum_{k=0}^{J} \mu_t^{j,k} L_t^k \tag{B-5}$$

[5]See section B.2 for detailed derivations.
[6]Notice that this notation includes those that decide to continue in the same sector, $\mu_{l,t}^{j,j}$.
[7]See section B.2 for details.

Production of Intermediate Goods

In each country n, a set of firms in each sector produce varieties of intermediate goods, combining composite labor l_t^{nj}, structures h_t^{nj} (a production factor which is analogous to physical capital but has a fixed supply[8] equal to H^{nj}), and sectoral aggregate inputs acquired from all sectors. The composite labor index l_t^{nj} is obtained by combining the two types of labor, u_t^{nj} and s_t^{nj}, through a Constant Elasticity of Substitution aggregator with elasticity of substitution given by σ, and a sector-specific share parameter δ^{nj}:

$$l_t^{nj} = \left[(\delta^{nj})^{\frac{1}{\sigma}}(u_t^{nj})^{\frac{\sigma-1}{\sigma}} + (1-\delta^{nj})^{\frac{1}{\sigma}}(s_t^{nj})^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}$$

The production function (which is Cobb-Douglas) has two productivity components: a sectoral one (A_t^{nj}), which varies across time but is the same for all firms in that sector, and a firm-specific term (z^{nj}, which will be used to index varieties), which is fixed in time but stochastic, following a Fréchet distribution with dispersion parameter θ^j; formally, the output of a variety is given by:

$$q_t^{nj} = z^{nj}\left(A_t^{nj}(h_t^{nj})^{\xi^n}(l_t^{nj})^{1-\xi^n}\right)^{\gamma^{nj}}\prod_{k=1}^{J}(M_t^{nj,nk})^{\gamma^{nj,nk}} \quad \text{(B-6)}$$

where $M_t^{nj,nk}$ is the amount of k-sector inputs used by a firm in n to produce q_t^{nj} units of a variety from sector j with firm-specific productivity z^{nj}. The production exhibits constant returns to scale, that is, $\sum_{k=1}^{J}\gamma^{nj,nk} + \gamma^{nj} = 1$.

The solution to the intermediate producer's problem implies that the unit price of an input bundle is given by

$$x_t^{nj} = B^{nj}((r_t^{nj})^{\xi^n}(w_t^{nj})^{1-\xi^n})^{\gamma^{nj}}\prod_{k=1}^{J}(P_t^{nk})^{\gamma^{nj,nk}} \quad \text{(B-7)}$$

where B^{nj} is a constant, r_t^{nj} is the rental price of structures, and w_t^{nj} is an agregate labor cost index which is a weighted sum of unskilled ($w_{u,t}^{nj}$) and skilled ($w_{s,t}^{nj}$) wages, given by:

$$w_t^{nj} = \left[\delta^{nj}(w_{u,t}^{nj})^{1-\sigma} + (1-\delta^{nj})(w_{s,t}^{nj})^{1-\sigma}\right]^{\frac{1}{1-\sigma}} \quad \text{(B-7)}$$

Therefore the unit cost of a variety produced with productivity z^{nj} is equal to $x_t^{nj}/[z^{nj}(A_t^{nj})^{\gamma^{nj}}]$.

[8] That is, the model features “capital” in the production function, but abstracts from capital accumulation.

Given the perfectly competitive environment, local unit price in country n of a given variety will be determined by the lowest unit cost (trade costs included) across all countries that can produce that variety. Trade costs (in a broad sense, including physical hurdles, such as distance and available, to institutional ones such as tariffs and non-tariff barriers) are modeled using the standard "iceberg" approach: in order to supply in country n a j-sector variety produced in country i, $\kappa_t^{nj,ij} \geq 1$ units of that variety must be produced ($\kappa_t^{nj,ij} = \infty$ for nontradable sectors). Therefore, denoting $z^j = (z^{ij}, ..., z^{Nj})$ the vector of productivities of a given variety across all N countries, its market price in country n will be given by:

$$p_t^{nj}(z^j) = \min_i \left\{ \frac{\kappa_t^{nj,ij} x_t^{ij}}{z^{ij}(A_t^{ij})^{\gamma^{ij}}} \right\}$$

Local Sectoral Aggregate Goods

In each country, all varieties of a given sector – acquired from the lowest cost supplier as described above – are aggregated in a "composite" sectoral good Q_t^{nj}, which is used locally both for final consumption and for inputs in the production of all sectors, according to the following aggregator:

$$Q_t^{nj} = \left(\int_{\mathbb{R}_+^N} (\tilde{q}_t^{nj}(z^j))^{1-1/\eta^{nj}} d\phi^j(z^j) \right)^{\eta^{nj}/(\eta^{nj}-1)}$$

where $\tilde{q}_t^{nj}(z^j)$ is the quantity demanded of variety z^j, and $\phi^j(z^j) = \exp\{-\sum_{n=1}^{N}(z^{nj})^{-\theta^j}\}$ is the joint distribution of the vector z^j of a variety's productivities across different origins (which collapses to $\phi^{jn}(z^{jn})$ in the case of nontradables, given that there is only one available source).

Local aggregator firms also operate in perfect competition, and their problem can be expressed as

$$\max_{\{\tilde{q}_t^{nj}(z^j)\}_{\mathbb{R}_+^N}} P_t^{nj} Q_t^{nj} - \int_{\mathbb{R}_+^N} p_t^{nj}(z^j) \tilde{q}_t^{nj}(z^j) d\phi^j(z^j)$$

The solution for this problem implies that the demand for a variety $\tilde{q}_t^{nj}(z^j)$ is given by:

$$\tilde{q}_t^{nj}(z^j) = \left(\frac{p_t^{nj}(z^j)}{P_t^{nj}} \right)^{\eta^{nj}} Q_t^{nj}$$

while the price of a sectoral composite is:

$$P_t^{nj} = \left[\int_{\mathbb{R}_+^N} (p_t^{nj}(z^j))^{1-\eta^{nj}} d\phi^j(z^j) \right]^{\frac{1}{1-\eta^{nj}}}$$

The properties of the Fréchet distribution allows us to express this price as[9]:

$$P_t^{nj} = \Gamma^{nj} \left(\sum_{i=1}^{N} (x_t^{ij} \kappa_t^{nj,ij})^{-\theta^j} (A_t^{ij})^{\theta^j \gamma^{ij}} \right)^{-1/\theta^j} \tag{B-8}$$

where Γ^{nj} is the Gamma function evaluated at $1 + (1 - \frac{\eta^{nj}}{\theta^j})$, a constant. Moreover, similarly to what was made above for the proportion of families changing sectors, it is possible to obtain a gravity-like equation for the fraction of expenditure in country n and sector j which is spent on varieties produced in country i, $\pi_t^{nj,ij}$ – which, as one may expect, will depend positively on productivity (that is, the higher A_t^{ij}, *ceteris paribus*, more will be spent on goods made in i) and negatively on transport costs:

$$\pi_t^{nj,ij} = \frac{(x_t^{ij} \kappa_t^{nj,ij})^{-\theta^j} (A_t^{ij})^{\theta^j \gamma^{ij}}}{\sum_{m=1}^{N} (x_t^{mj} \kappa_t^{nj,mj})^{-\theta^j} (A_t^{mj})^{\theta^j \gamma^{mj}}} \tag{B-9}$$

Market Clearing

The model accounts for the possibility of trade deficits by assuming the existence, in each country, of an unit mass of structure owners, which cannot migrate, and are paid the market rate r_t^{ik}; the revenue of all structure owners is deposited in a global fund in exchange for a constant share ι^n (with $\sum_{n=1}^{N} \iota^n = 1$) of this portfolio, which they use to consume local aggregates according to (B-1). Trade imbalances, therefore, stem from the differences between structures rental revenues and the shares received by structures owners in each country, and are defined as $\sum_{k=1}^{J} r_t^{nk} H^{nk} - \iota^n \sum_{i=1}^{N} \sum_{k=1}^{J} r_t^{ik} H^{ik}$.

The market for each of the primary factors (structures and the two types of labor) clear if the factor's total payments equals its share in total value added; so, for structures we have:

$$H^{nj} r_t^{nj} = \gamma^{nj} \xi^n \sum_{i=1}^{N} \pi^{ij,nj} X_t^{ij} \tag{B-10}$$

and for labor we have one condition for each type:

[9]Detailed derivation in Appendix B.2. In order to obtain (B-8), we assume $1 + \theta^j > \eta^{nj}$.

$$U_t^{nj} w_{t,u}^{nj} = \upsilon_t^{nj} \gamma^{nj} (1 - \xi^n) \sum_{i=1}^{N} \pi^{ij,nj} X_t^{ij} \tag{B-11}$$

for unskilled labor, and

$$S_t^{nj} w_{t,s}^{nj} = (1 - \upsilon_t^{nj}) \gamma^{nj} (1 - \xi^n) \sum_{i=1}^{N} \pi^{ij,nj} X_t^{ij} \tag{B-12}$$

Since goods are used both for final consumption and as inputs in production, market clearing in the goods market implies that total expenditures in sector j in country n (denoted X_t^{nj}) must equal the sum of final intermediate demand at home plus intermediate consumption in every country; formally,

$$\begin{aligned} X_t^{nj} = {} & \textstyle\sum_{k=1}^{J} \gamma^{nk,nj} \sum_{i=1}^{N} \pi^{ik,nk} X_t^{ik} + \\ & \alpha^j \left(\textstyle\sum_{k=1}^{J} (w_{t,u}^{nk} U_t^{nk} + w_{t,s}^{nk} S_t^{nk}) + \iota^n \sum_{i=1}^{N} \sum_{k=1}^{J} r_t^{ik} H^{ik} \right) \end{aligned} \tag{B-13}$$

Equilibrium

It is useful to approach the definition of equilibrium in a step-wise fashion that accounts for the nature of the model, which embeds successive trade models in each period of a dynamic occupational choice structure. Therefore, we can define separately the equilibrium of the static subproblems (taking as given the period's state of the dynamic problem) and that of the dynamic problem (which also requires that all static subproblems are solved at each period)[10].

Finding the equilibrium in each static subproblem consists in obtaining wages $w_{l,t} = \{w_{l,t}^{nj}\}_{n=1,j=1}^{N,J}$, $l \in \{U, S\}$ and allocations $\pi_t = \{\pi_t^{ij,nj}\}_{n=1,i=1,j=1}^{N,N,J}$ and $X_t = \{X_t^{nj}\}_{n=1,j=1}^{N,J}$ that solve the agents' problems and clears all markets in the trade model, taking as given the period's value of the state variables U_t, S_t, the sets of time-variable ($\Theta_t \equiv (A_t, \kappa_t)$) and fixed ($\bar{\Theta} \equiv (\Upsilon, H, b)$) deterministic fundamentals of the economy, and parameters $\{\alpha_j, \gamma^{nj}, \xi^n, \gamma^{nk,nj}, \iota^n, \beta, \nu, \theta^j\}$. More concisely, the temporary equilibrium is the vector of wages $w(U_t, S_t, \Theta_t, \bar{\Theta})$ that satisfies the static equilibrium conditions (B-7) to (B-13), given $(U_t, S_t, \Theta_t, \bar{\Theta})$.

As for the dynamic problem, the equilibrium involves not only the sequences of equilibrium wages and allocations that solve the trade model

[10]See CDP and references therein for proofs of the existence and uniqueness of the two types of equilibrium.

in each period, but also the paths of each labor's allocations – which is described by the sequences of labor allocations, $U_t = \{U_t^j\}_{j=1}^J$ and $S_t = \{S_t^j\}_{j=1}^J$, and labor transition matrices, $\mu_{l,t} = \{\mu_{l,t}^{j,k}\}_{j=1,k=1}^{J,J}$ –, as well as the sequence of lifetime utilities ($V_{l,t} = \{V_{l,t}^{nj}\}_{n=1,j=1}^{N,J}$) that solves the households' problem. That is, a **sequential equilibrium** for the model is a sequence of $\{U_t, S_t, \mu_{u,t}, \mu_{s,t}, V_{u,t}, V_{s,t}, w(U_t, S_t, \Theta_t, \bar{\Theta})\}_{t=0}^{\infty}$ which satisfies the dynamic equilibrium conditions (B-2) to (B-4), while also being temporary equilibria for each period, given $(U_t, S_t, \{\Theta_t\}_{t=0}^{\infty}, \bar{\Theta})$. In particular, we can define a **stationary equilibrium** for the model as a sequential equilibrium in which the sequence $\{U_t, S_t, \mu_{u,t}, \mu_{s,t}, V_{u,t}, V_{s,t}, w(U_t, S_t, \Theta_t, \bar{\Theta})\}_{t=0}^{\infty}$ is constant $\forall\ t$ – notice that, in this case, all inward and outward flows of labor across sectors must cancel each other, so that the path of labor stays constant.

B.1.2 Dynamic Hat Algebra

As discussed in the main text, CDP show that, under certain hypotheses, it is possible to rewrite the model's equilibrium conditions in terms of *time differences* – that is, $\dot{x}_{t+1} \equiv \frac{x_{t+1}}{x_t}$ – in order to find the model's solution by conditioning in usually available data – on bilateral trade flows and labor transitions, for example – with no needing to obtain unavailable information on levels of variables such as productivity and trade costs. Moreover, we can rewrite the model in terms of *ratios of time changes* between baseline and counterfactual – that is, $\hat{x}_{t+1} \equiv \frac{\dot{x'}_{t+1}}{\dot{x}_{t+1}}$, where $\dot{x'}_{t+1} \equiv \frac{x'_{t+1}}{x'_t}$ are the time differences in counterfactual equilibrium – in order to obtain the sequences of counterfactual values of interest variables, given any postulated change in the time path of any set of the model fundamentals – again, without the need to know or estimate the levels of those fundamentals. We now describe the rewritten equilibrium conditions[11].

Static Sub-Problem

The equilibrium conditions of the static subproblem, (B-7) to (B-13), can be expressed in terms of time differences as follows:

[11] The complete proofs are in Propositions 1-3 in Caliendo et al. (2019)

$$\dot{w}^{nj}_{t+1} = \left[\upsilon^{nj}_t(\dot{w}^{nj}_{u,t+1})^{1-\sigma} + (1-\upsilon^{nj}_t)(\dot{w}^{nj}_{s,t+1})^{1-\sigma}\right]^{\frac{1}{\sigma-1}} \tag{B-14}$$

$$\dot{x}^{nj}_{t+1} = (\dot{L}^{nj}_{t+1})^{\gamma^{nj}\xi^n}(\dot{w}^{nj}_{t+1})^{\gamma^{nj}}\prod_{k=1}^{J}(\dot{P}^{nk}_{t+1})^{\gamma^{nj,nk}} \tag{B-15}$$

$$\dot{P}^{nj}_{t+1} = \left(\sum_{i=1}^{N}\pi^{nj,ij}_t(\dot{x}^{nj}_{t+1}\dot{\kappa}^{nj,ij}_{t+1})^{\theta^j}(\dot{A}^{ij}_{t+1})^{\theta^j\gamma^{ij}}\right)^{-1/\theta^j} \tag{B-16}$$

$$\pi^{nj,ij}_{t+1} = \pi^{nj,ij}_t\left(\frac{\dot{x}^{ij}_{t+1}\dot{\kappa}^{ij}_{t+1}}{\dot{P}^{nj}_{t+1}}\right)^{\theta^j}(\dot{A}^{ij}_{t+1})^{\theta^j\gamma^{ij}} \tag{B-17}$$

$$X^{nj}_{t+1} = \sum_{k=1}^{J}\gamma^{nk,nj}\sum_{i=1}^{N}\pi^{ik,nk}_{t+1}X^{ik}_{t+1} + \alpha^j\left(\sum_{k=1}^{J}\dot{w}^{nk}_{t+1}\dot{L}^{nk}_{t+1}w^{nk}_tL^{nk}_t + \iota^n\chi_{t+1}\right) \tag{B-18}$$

$$\dot{w}^{nk}_{u,t+1}\dot{U}^{nk}_{t+1} = \frac{\upsilon^{nj}_t\gamma^{nj}(1-\xi^n)}{w^{nk}_{u,t}U^{nk}_t}\sum_{i=1}^{N}\pi^{ik,nk}_{t+1}X^{ik}_{t+1} \tag{B-19}$$

$$\dot{w}^{nk}_{s,t+1}\dot{S}^{nk}_{t+1} = \frac{\upsilon^{nj}_t\gamma^{nj}(1-\xi^n)}{w^{nk}_{s,t}S^{nk}_t}\sum_{i=1}^{N}\pi^{ik,nk}_{t+1}X^{ik}_{t+1} \tag{B-20}$$

where $\chi_{t+1} = \sum_{i=1}^{N}\sum_{k=1}^{J}\frac{\xi^i}{1-\xi^i}\dot{w}^{nk}_{t+1}\dot{L}^{nk}_{t+1}w^{nk}_tL^{nk}_t$

It is easy to notice that, given an allocation $\{L_t, \pi_t, X_t\}$ in period t and a vector of time changes in $\dot{L}_{t+1}$ and $\dot{\Theta}_{t+1}$, it is possible to solve sequentially to the vectors of prices and equilibrium allocations without any information on levels of fundamentals Θ_t or $\bar{\Theta}$, which do not show in the modified static equilibrium conditions (B-15)-(**??**).

Dynamic Problem

Similarly, one can rewrite in terms of time differences the sequential equilibrium conditions (B-2) to (B-4) – one additional necessary assumption, however, is that preferences are logarithmic, that is, $U(C^{nj}_t) \equiv \log(C^{nj}_t)$. Denoting, for convenience, $u^{nj}_t \equiv \exp(V^{nj}_t)$, we can obtain the following sets modified equilibrium conditions, for $l \in \{U, S\}$:

$$\mu^{nj,ik}_{l,t+1} = \frac{\mu^{nj,ik}_{l,t}(\dot{u}^{ik}_{l,t+2})^{\beta/\nu_l}}{\sum_{m=1}^{N}\sum_{h=1}^{J}\mu^{nj,mh}_{l,t}(\dot{u}^{mh}_{l,t+2})^{\beta/\nu_l}} \tag{B-21}$$

$$\dot{u}^{nj}_{l,t+1} = \frac{\dot{w}^{nj}_{l,t+1}}{\dot{P}^{nj}_{t+1}}\left(\sum_{m=1}^{N}\sum_{h=1}^{J}\mu^{nj,mh}_{l,t}(\dot{u}^{mh}_{l,t+2})^{\beta/\nu}\right)^{\nu_l} \tag{B-22}$$

$$L^{nj}_{l,t+1} = \sum_{i=1}^{N}\sum_{k=1}^{J}\mu^{ik,nj}_{l,t}L^{ik}_{l,t} \tag{B-23}$$

where $\dot{w}^{nj}_{t+1}/\dot{P}^{nj}_{t+1}$ is obtained in the solution to the static sub-problem described above. So, given an initial allocation $\{S_0, U_0, \pi_0, X_t, \mu_{-1}\}$ and a converging sequence of changes in fundamentals $\{\dot{\Theta}_{t+1}\}_{t=1}^{\infty}$[12], we can obtain the sequence of labor allocations, sectoral labor transition matrices, and lifetime utilities that solve the households' dynamic problem, with no need for information on the levels of fundamentals $\{\Theta_t\}_{t=1}^{\infty}$ e $\bar{\Theta}$.

Solving for Counterfactuals

Finally, we can rewrite the modified equilibrium conditions (B-15)-(B-23) using ratios of time differences – that is, the ratio between the counterfactual and baseline time differences of a given variable; formally, $\hat{x}_{t+1} \equiv \frac{\dot{x}'_{t+1}}{\dot{x}_{t+1}}$, where $\dot{x}$ is the baseline time difference in x, and x' denotes the counterfactual value of a variable. Therefore, given a baseline equilibrium $\{L_t, \mu_{t-1}, \pi_t, X_t\}_{t=1}^{\infty}$ and a converging sequence of ratios of time differences in relation to this baseline $\{\dot{\Theta}_{t+1}\}_{t=1}^{\infty}$, we can solve for the counterfactual sequence of equilibrium allocations, $\{L'_t, \mu'_{t-1}, \pi'_t, X'_t\}_{t=1}^{\infty}$, without information on baseline levels of fundamentals, using the following system of equations:

$$\mu'^{nj,ik}_{l,t} = \frac{\mu'^{nj,ik}_{l,t-1}\,\dot{\mu}^{nj,ik}_{l,t}\,(\hat{u}^{ik}_{l,t+1})^{\beta/\nu_l}}{\sum_{m=1}^{N}\sum_{h=1}^{J}\mu'^{nj,mh}_{l,t-1}\,\dot{\mu}^{nj,mh}_{l,t}\,(\hat{u}^{mh}_{l,t+1})^{\beta/\nu_l}} \tag{B-24}$$

$$\dot{u}^{nj}_{l,t} = \frac{\hat{w}^{nj}_{l,t+1}}{\hat{P}^{nj}_{t+1}}\left(\sum_{m=1}^{N}\sum_{h=1}^{J}\mu'^{nj,mh}_{l,t-1}\,\dot{\mu}^{nj,mh}_{l,t}\,(\hat{u}^{mh}_{l,t+1})^{\beta/\nu_l}\right)^{\nu_l} \tag{B-25}$$

$$L'^{nj}_{l,t+1} = \sum_{i=1}^{N}\sum_{k=1}^{J}\mu'^{ik,nj}_{l,t}\,L'^{ik}_{l,t} \tag{B-26}$$

$l \in \{U, S\}$, for the sequential equilibrium, and

[12]That is, such that $\lim_{t\to\infty}\dot{\Theta}_t = 1$.

$$\hat{w}^{nj}_{t+1} = \left[\upsilon^{'nj}_t (\hat{w}^{nj}_{u,t+1})^{1-\sigma} + (1-\upsilon^{'nj}_t)(\hat{w}^{nj}_{s,t+1})^{1-\sigma}\right]^{\frac{1}{\sigma-1}} \quad \text{(B-27)}$$

$$\hat{x}^{nj}_{t+1} = (\hat{L}^{nj}_{t+1})^{\gamma^{nj}\xi^n} (\hat{w}^{nj}_{t+1})^{\gamma^{nj}} \prod_{k=1}^{J} (\hat{P}^{nk}_{t+1})^{\gamma^{nj,nk}} \quad \text{(B-28)}$$

$$\hat{P}^{nj}_{t+1} = \left(\sum_{i=1}^{N} \pi^{'nj,ij}_t \dot{\pi}^{nj,ij}_{t+1} (\hat{x}^{ij}_{t+1}\hat{\kappa}^{nj,ij}_{t+1})^{-\theta^j} (\hat{A}^{ij}_{t+1})^{\theta^j\gamma^{ij}}\right)^{-1/\theta^j} \quad \text{(B-29)}$$

$$\pi^{'nj,ij}_{t+1} = \pi^{'nj,ij}_t \pi^{nj,ij}_{t+1} \left(\frac{\hat{x}^{ij}_{t+1}\hat{\kappa}^{ij}_{t+1}}{\hat{P}^{nj}_{t+1}}\right)^{-\theta^j} (\hat{A}^{ij}_{t+1})^{\theta^j\gamma^{ij}} \quad \text{(B-30)}$$

$$X^{'nj}_{t+1} = \sum_{k=1}^{J} \gamma^{nk,nj} \sum_{i=1}^{N} \pi^{'ik,nk}_{t+1} X^{'ik}_{t+1} + \alpha^j \left(\sum_{k=1}^{J} \hat{w}^{nk}_{t+1}\hat{L}^{nk}_{t+1} w^{'nk}_t L^{'nk}_t \dot{w}^{nk}_{t+1}\dot{L}^{nk}_{t+1} + \iota^n \chi^{'}_{t+1}\right) \quad \text{(B-31)}$$

$$\hat{w}^{nk}_{u,t+1}\hat{U}^{nk}_{t+1} = \frac{\upsilon^{'nj}_t \gamma^{nj}(1-\xi^n)}{w^{'nk}_{u,t} U^{'nk}_t \dot{w}^{nk}_{u,t+1}\dot{U}^{nk}_{t+1}} \sum_{i=1}^{N} \pi^{ik,nk}_{t+1} X^{ik}_{t+1} \quad \text{(B-32)}$$

$$\upsilon^{'nj}_{t+1} = \left[1 + \frac{(1-\upsilon^{'nj}_t)}{\upsilon^{'nj}_t}\left(\frac{\dot{w}^{nj}_{u,t+1}}{\dot{w}^{nj}_{s,t+1}}\right)^{\sigma-1}\right]^{-1} \quad \text{(B-33)}$$

for the temporary equilibrium at every time t, where $\chi^{'}_{t+1} = \sum_{i=1}^{N}\sum_{k=1}^{J} \frac{\xi^i}{1-\xi^i} \hat{w}^{ik}_{t+1}\hat{L}^{ik}_{l,t+1} w^{'ik}_{l,t} L^{'ik}_{l,t} \dot{w}^{ik}_{l,t+1}\dot{L}^{ik}_{l,t+1}$. Thus, using the modified equilibrium conditions (B-15)-(B-33), one can obtain, given time series of data representing the baseline equilibrium and hypotheses about the time path of fundamentals in the counterfactual scenario *vis-à-vis* the baseline equilibrium (and also, of course, estimates of the parameters of the model), it is possible to simulate the model and perform counterfactual exercises without knowing the full set of fundamentals in the economy. The simulation follows the algorithm devised by CDP and described in its Appendix D.

B.2 Additional Derivations

B.2.1 Household's Problem

Note[13] from the household's dynamic problem that in order to obtain the expected utility $V^j_t \equiv E[v^k_t]$ we need to solve for the part of the problem that depends on ϵ, ie, the continuing value that depends on future idiosyncratic shocks, which we can denote as:

$$\Psi^j_t = E\left[\max_k \{\beta E[v^k_{t+1}] - \tau^{j,k} + \nu\epsilon^k_t\}\right]$$

[13]This and the next section follow the derivation on Caliendo et al. (2019) and Caliendo and Parro (2015)

Consider a third labor market h, and define $\bar{\epsilon}_t^{k,h} \equiv \epsilon_t^h - \epsilon_t^k$ as the differential idiosyncratic shock that would leave the household indifferent between moving from j to either k or h; that is,

$$\beta V_{t+1}^k - \tau^{j,k} + \nu\epsilon_t^k - (\beta V_{t+1}^h - \tau^{j,h}) + \nu\epsilon_t^h) = 0$$

and therefore

$$\bar{\epsilon}_t^{k,h} = \frac{1}{\nu}\left[\beta(V_{t+1}^k - V_{t+1}^h) - (\tau^{j,k} - \tau^{j,h})\right]$$

Therefore we can express the expectation of the maximum in Ψ_t^j as:

$$\Psi_t^j = \sum_{k=0}^{J} \int_{-\infty}^{\infty} (\beta V_{t+1}^k - \tau^{j,k} + \nu\epsilon_t^k) f(\epsilon_t^k) \prod_{h \neq k} F(\bar{\epsilon}_t^{k,h} + \epsilon_t^k) d\epsilon_t^k$$

From the distributional hypothesis on the idiosyncratic shock, we have $F(\epsilon) = \exp(-\exp(-\epsilon - \bar{\gamma})$ (where $\bar{\gamma}$ is Euler's constant), and $f(\epsilon) = \exp(-\exp(-\epsilon - \bar{\gamma}) - \epsilon - \bar{\gamma})$; substituting into the last equation we'll have:

$$\Psi_t^j = \sum_{k=0}^{J} \int_{-\infty}^{\infty} (\beta V_{t+1}^k - \tau^{j,k} + \nu\epsilon_t^k) \exp(-\exp(-\epsilon_t^k - \bar{\gamma}) \prod_{h \neq k} \exp(-\exp(-\bar{\epsilon}_t^{k,h} - \epsilon_t^k - \bar{\gamma}) d\epsilon_t^k$$

Multiplying by $\exp(-\bar{\epsilon}_t^{k,h}) = 1$ and rearranging, we can complete the product in the right-hand side:

$$\Psi_t^j = \sum_{k=0}^{J} \int_{-\infty}^{\infty} (\beta V_{t+1}^k - \tau^{j,k} + \nu\epsilon_t^k) \exp(-\epsilon_t^k - \bar{\gamma}) \prod_{h=1}^{J} \exp(-\exp(-\bar{\epsilon}_t^{k,h} - \epsilon_t^k - \bar{\gamma}) d\epsilon_t^k$$

and rearrange to obtain:

$$\Psi_t^j = \sum_{k=0}^{J} \int_{-\infty}^{\infty} (\beta V_{t+1}^k - \tau^{j,k} + \nu\epsilon_t^k) \exp(-\epsilon_t^k - \bar{\gamma}) \exp\left(-\exp(-\epsilon_t^k - \bar{\gamma}) \sum_{h=1}^{J} \exp(-\bar{\epsilon}_t^{k,h})\right) d\epsilon_t^k$$

Defining $\lambda_t^k = \log \sum_{h=1}^{J} \exp(-\bar{\epsilon}_t^{k,h})$ and $\xi_t^k = \epsilon_t^k + \bar{\gamma}$, we get:

$$\Psi_t^j = \sum_{k=0}^{J} \int_{-\infty}^{\infty} (\beta V_{t+1}^k - \tau^{j,k} + \nu(\xi_t^k - \bar{\gamma})) \exp\left(\xi_t^k - \exp(-(\xi_t^k - \lambda_t^k))\right) d\xi_t^k$$

Changing variables again to $\tilde{y}_t^k = \xi_t^k - \lambda_t^k$, we obtain:

$$
\begin{aligned}
\Psi_t^j &= \sum_{k=0}^{J} \int_{-\infty}^{\infty} (\beta V_{t+1}^k - \tau^{j,k} + \nu(\tilde{y}_t^k + \lambda_t^k - \bar{\gamma})) \exp\left(-\tilde{y}_t^k - \lambda_t^k - \exp(-(-\tilde{y}_t^k))\right) d\tilde{y}_t^k \\
&= \sum_{k=0}^{J} \exp(-\lambda_t^k) \left[(\beta V_{t+1}^k - \tau^{j,k} + \nu(\lambda_t^k - \bar{\gamma})) + \nu \int_{-\infty}^{\infty} \tilde{y}_t^k \exp\left(-\tilde{y}_t^k - \exp(-\tilde{y}_t^k)\right) d\tilde{y}_t^k\right]
\end{aligned}
$$

But notice that the integral in the right-hand side is simply the Euler constant $\bar{\gamma}$, so this expression collapses to:

$$
\begin{aligned}
\Psi_t^j &= \sum_{k=0}^{J} \exp(-\lambda_t^k) \left(\beta V_{t+1}^k - \tau^{j,k} + \nu(\lambda_t^k - \bar{\gamma})) + \nu\bar{\gamma}\right) \\
&= \sum_{k=0}^{J} \exp(-\lambda_t^k) \left(\beta V_{t+1}^k - \tau^{j,k} + \nu\lambda_t^k\right)
\end{aligned}
$$

Substituting back λ_t^k and $\bar{\epsilon}_t^{k,h} \equiv \epsilon_t^h - \epsilon_t^k$ and rearranging, we'll obtain:

$$\Psi_t^j = \nu \left(\log \sum_{k=0}^{J} \exp(\beta V_{t+1}^k - \tau^{j,k})\right)$$

Substituting this back into the household's problem, we'll end up with equation (B-2):

$$V_t^j = U(C_j^j) + \nu log \left(\sum_{k=0}^{J} exp(\beta V_{t+1}^k - \tau^{j,k})^{1/\nu}\right)$$

To obtain equation B-3, first notice that it is the probability that the expected utility in sector k is the largest among all sectors, or

$$
\begin{aligned}
\mu_t^{j,k} &= \mathbb{P}\left[\beta V_{t+1}^k - \tau^{j,k} + \nu\epsilon_t^k \geq \max_{h \neq k} \left(\beta V_{t+1}^h - \tau^{j,h} + \nu\epsilon_t^h\right)\right] \\
&= \int_{-\infty}^{\infty} f(\epsilon_t^k) \prod_{h \neq k} F(\beta(V_{t+1}^k - V_{t+1}^h) - (\tau^{j,k} - \tau^{j,h}) + \epsilon_t^k) d\epsilon_t^k \\
&= \int_{-\infty}^{\infty} f(\epsilon_t^k) \prod_{h \neq k} F(\bar{\epsilon}_t^{k,h} + \epsilon_t^k) d\epsilon_t^k
\end{aligned}
$$

Substituting, as before, the expressions for the CDF and PDF of the shock, we'll get:

$$\mu_t^{j,k} = \int_{-\infty}^{\infty} \exp(-\exp(-\epsilon_t^k - \bar{\gamma})) \prod_{h \neq k} \exp(-\exp(-\bar{\epsilon}_t^{k,h} - \epsilon_t^k - \bar{\gamma})) d\epsilon_t^k$$

Following similar steps as above, this can be rearranged to:

$$\mu_t^{j,k} = \int_{-\infty}^{\infty} \exp(-\epsilon_t^k - \bar{\gamma}) exp(-exp(-\epsilon_t^k - \bar{\gamma}) \sum_{h=0}^{J} \exp(-\bar{\epsilon}_t^{k,h})) d\epsilon_t^k$$

Using the same variable substitutions as before, this can be rewritten as:

$$\begin{aligned}\mu_t^{j,k} &= \exp(\lambda_t^k) \int_{-\infty}^{\infty} \exp(-\tilde{y}_t^k - \exp(-\tilde{y}_t^k)) d\tilde{y}_t^k \\ &= \exp(\lambda_t^k)\end{aligned}$$

where the second equality follows from the fact that the integral is equal to one. Substituting back λ_t^k and $\bar{\epsilon}_t^{k,h}$ and rearranging, we'll obtain:

$$\begin{aligned}\mu_t^{j,k} &= \exp\left(-\log \sum_{h=0}^{J} \exp\left((\tau^{j,k} - \tau^{j,h}) - \beta(V_{t+1}^k - V_{t+1}^h)\right)\right)^{1/\nu} \\ &= \exp(-\log(\exp(-\beta V_{t+1}^k - \tau^{j,k})^{1/\nu} \exp\left(-\log \sum_{h=0}^{J} \exp(\beta V_{t+1}^h - \tau^{j,h})^{1/\nu}\right) \\ &= \frac{\exp(\beta V_{t+1}^k - \tau^{j,k})^{1/\nu}}{\sum_{h=0}^{J} \exp(\beta V_{t+1}^h - \tau^{j,h})^{1/\nu}}\end{aligned}$$

which is equation (B-3).

B.2.2
Local Sectoral Aggregate Goods

In order to reduce notational clutter, we will omit the time subscript and the region and sector superscript, except for the one that refers to a good's origin; that is, we'll denote, for example, by $p^i(z) \equiv p_t^{nj,ij}$ the price of a variety z of sector j made in country i and sold in n, and similarly for bilateral iceberg costs $\kappa^i(z) \equiv \kappa_t^{nj,ij}$, input price $x^i \equiv x_t^{ij}$, etc. The price of a sectoral composite in a given time, region and sector is defined by:

$$P^{1-\eta} = \int_{\mathbb{R}_+^N} p(z)^{1-\eta} d\phi(z)$$

which is the expected value of the random variable $p(z)^{1-\eta}$. Given the distributional assumptions about $\phi(z)$, we'll have:

$$\begin{aligned}
\mathbb{P}\left[p^i(z) \le p\right] &= \mathbb{P}\left[\frac{\kappa^i x^i}{z^i (A^i)^{\gamma^i}} \le p\right] = \mathbb{P}\left[z^i \ge \frac{\kappa^i x^i}{p(A^i)^{\gamma^i}}\right] = 1 - \mathbb{P}\left[z^i \le \frac{\kappa^i x^i}{p(A^i)^{\gamma^i}}\right] \\
&= 1 - \phi\left(\frac{\kappa^i x^i}{p(A^i)^{\gamma^i}}\right) \\
&= 1 - \exp\left[-\left(\frac{\kappa^i x^i}{p(A^i)^{\gamma^i}}\right)^{-\theta}\right] \\
&= 1 - \exp(-\lambda^i p^\theta)
\end{aligned}$$

where we define $\lambda^i = \left(\frac{\kappa^i x^i}{(A^i)^{\gamma^i}}\right)^{-\theta}$.
Therefore,

$$\begin{aligned}
\mathbb{P}\left[p(z) \le p\right] &= \mathbb{P}\left[\min_i\{p^i(z)\} \le p\right] = 1 - \mathbb{P}\left[\min_i\{p^i(z)\} > p\right] \\
&= 1 - \prod_{n=1}^{N} \mathbb{P}\left[p^n(z) > p\right] \\
&= 1 - \prod_{n=1}^{N} \mathbb{P}\left[z^n \le \frac{\kappa^n x^n}{p(A^n)^{\gamma^n}}\right] \\
&= 1 - \prod_{n=1}^{N} \exp(-\lambda^n p^\theta) \\
&= 1 - \exp(-\Phi p^\theta)
\end{aligned}$$

where $\Phi = \sum_{n=1}^{N} \lambda^n$. The PDF associated with the CDF defined by $\mathbb{P}\left[p(z) \le p\right]$ is, therefore, the derivative of this expression: $f(p) = \Phi\theta p^{\theta-1}\exp(-\Phi p^\theta)$. Moreover, defining $y = g(p) = p^\theta$, the PDF of p^θ is given by $f_y(y) = \Phi\exp(-\Phi y)$.

We can then write the expected value in the definition of the price of a sectoral composite in terms of the distribution of p^θ as:

$$\begin{aligned}
P^{1-\eta} &= \int_{-\infty}^{\infty} p(z)^{1-\eta} f(p)dp = \int_{-\infty}^{\infty} p^{1-\eta}\Phi\theta p^{\theta-1}\exp(-\Phi p^\theta)dp \\
&= \int_{-\infty}^{\infty} (p^\theta)^{(1-\eta)/\theta}\Phi\theta p^{\theta-1}\exp(-\Phi p^\theta)dp \\
&= \int_{-\infty}^{\infty} y^{(1-\eta)/\theta}\Phi\exp(-\Phi y)dy
\end{aligned}$$

Defining $u = \Phi y$ (so that $du = \Phi dy$), we'll have:

$$
\begin{aligned}
P^{1-\eta} &= \int_{-\infty}^{\infty} \left(\frac{u}{\Phi}\right)^{(1-\eta)/\theta} \exp(-u)du = \Phi^{(\eta-1)/\theta} \int_{-\infty}^{\infty} u^{(1-\eta)/\theta} \exp(-u)du \\
&= \Phi^{(\eta-1)/\theta}\Gamma\left(1 + \frac{1-\eta}{\theta}\right)
\end{aligned}
$$

where in the last step we use the definition of the Gamma function $\Gamma(a) = \int_{-\infty}^{\infty} b^{a-1} \exp(-b)db$.

Substituting back the definitions of Φ and λ we'll obtain the expression for the price of the sectoral aggregate good j in region n at time t given by equation (B-8).

C
Appendix to Chapter 3

C.1
Assessing the Effect of Non-Automatic Licensing on Trade

The main results in this paper present evidence supporting the hypothesis that industries with larger trade associations show higher prevalence of one type of non-tariff measure – non-automatic licensing – that may provide protection from foreign competition. Thus, it remains to be showed that imposing non-automatic licenses indeed harms trade.

In principle, WTO rules dictates non-automatic licensing should be used to administer other measures such as technical or quantitative restrictions, and should have no additional restrictive or distorting effects on imports. In practice, however, these licenses can be – and actually are – used as short-term protectionist measures. Grosso (2005) argues that non-automatic licenses have been extensively used to control imports for economic reasons, especially by developing countries seeking to alleviate balance-of-payment problems.

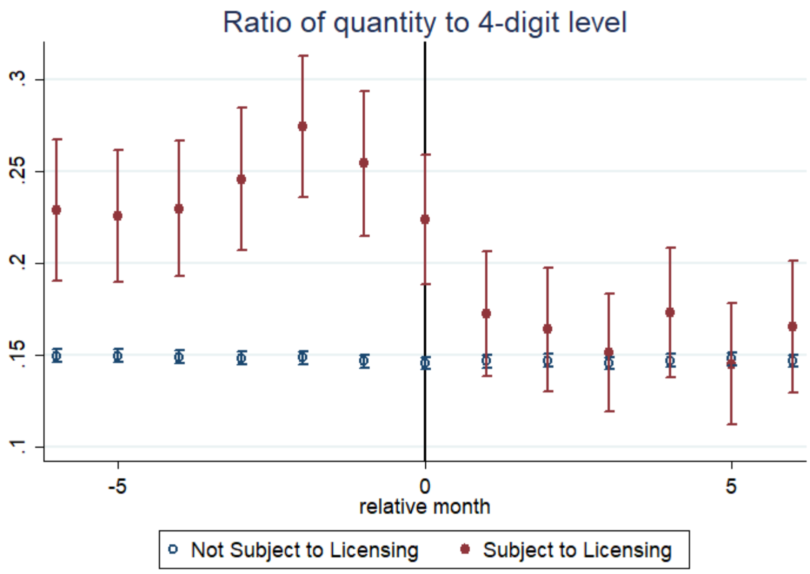
Nevertheless, direct evidence on the effect of non-automatic licensing on trade flows is scarce. One possible reason for this lack of evidence is the fact that most trade data are annual; therefore, if this type of non-tariff measure is indeed a short-term relief for a surge in imports, its effect may not appear clearly in trade flows. Consider a simple example: suppose that the imports of a given good in some country increases, say, by 100% in the first quarter of a given year; officials, then, impose non-automatic licensing for this good, and imports are reduced to the initial level for the remainder of that year. In this case, even though the adoption of the measure successfully reduced imports, annual data would point to an increase in total imports for that year, so that a gravity model – which is usually employed to gauge the effects of non-tariff measures on trade – would capture a positive correlation between licensing and trade volumes. Thus, one needs more detailed data.

In order to try to gauge more effectively the trade effects of licensing, although in a preliminary way and in a limited setting, we used a dataset that comprises non-automatic licensing imposed between 2006 and 2009 by the Brazilian Department of Foreign Trade (DECEX), from the Foreign Trade

Secretariat of the former Ministry of Development, Industry and Foreign Trade (SECEX/MDIC). This dataset contains a list of products – at the 8-digit level of the Mercosur Common Nomenclature (NCM, based on the Harmonized System of Commodity Description and Coding) – which were subject to non-automatic licensing, the date of imposition, and the origin countries affected. This allows the use of monthly trade data – which is made openly available by SECEX – to assess the effect of the license in an event-study type setting.

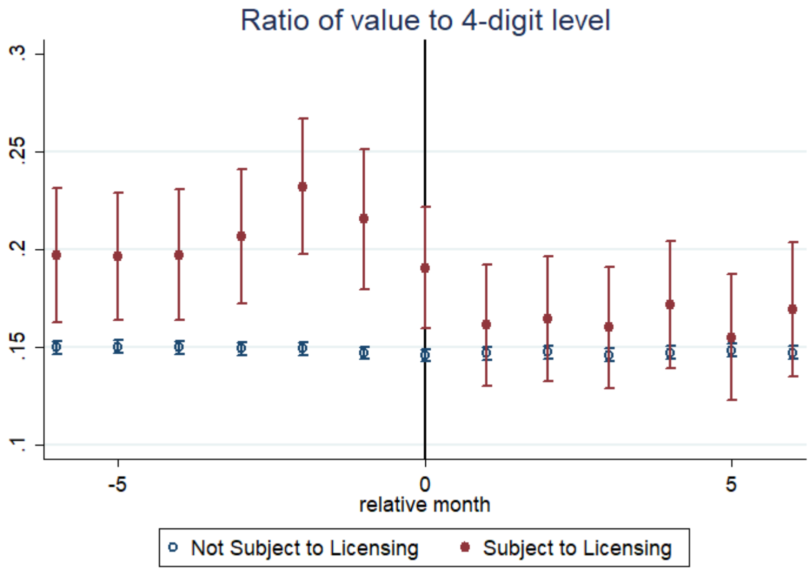
We take advantage of the nested structure of the Harmonized System in order to build a control group, by comparing the 8-digit product that was subject to the license to the remaining 8-digit codes under the same 4-digit heading[1] First, we compare the magnitudes, as a share of the 4-digit total, of import flows of 8-digit products affected by licensing to those not affected, before and after the measure – both in quantity (Figure C.1) and value (Figure C.2) terms. The plots clearly suggest that the import levels of "treated" products decline after the imposition *vis-à-vis* its 4-digit total, while no difference is visible for the "control" group.

Figure C.1: Non-Automatic Licensing – Effect on Quantity Imported



[1]For example, we compare "single or untwisted nylon yarns" (NCM 5402.45.20) with other "synthetic filament yarns not put up for retail sale" (NCM heading 5402), such as "raw polyester yarns" (NCM 5402.33.10).

Figure C.2: Non-Automatic Licensing – Effect on Value of Imports



Next, we regress 8-digit unit values, as well as the quantity and value ratios to the 4-digit totals, against dummies for the presence of non-automatic licenses, the periods after the imposition of the license, and interactions of the two – the latter being the coefficient of interest. We run these regressions for different time frames around the imposition of the measures, in order to see if the effects seem to fade out with time. Results on table C.1 suggest that this seems to be the case, with the increase in unit value and reduction in the share of trade flows decreasing in magnitude as we increase the time windows; however, the effect is still visible if we include one year before and after the adoption of the license.

Table C.1: Non-Automatic Licensing – Effect on Trade

Variables	(1) Unit Value	(2) Ratio to 4-digit level: Quantity	(3) Ratio to 4-digit level: Value (FOB)
3-month window			
treatXpost	2,399.213	-0.091	-0.071
	(916.540)***	(0.029)***	(0.029)**
6-month window			
treatXpost	2,706.464	-0.085	-0.071
	(917.942)***	(0.027)***	(0.026)***
9-month window			
treatXpost	2,606.440	-0.072	-0.061
	(866.894)***	(0.027)***	(0.026)**
12-month window			
treatXpost	2,411.737	-0.063	-0.053
	(766.159)***	(0.025)**	(0.025)**

Robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.2 Extension – Trade Associations vs. Campaign Contributions

This section examines the role of campaign contributions as a different potential mechanism for establishing political connections and its relationship with employer unions. The specifications adopted are similar to those of the main results, but with the industry-level measures of campaign donations (total contributions and average contribution per firm) as the outcome variables. Industry and period fixed effects are included in all specification; now, however, the time interval is one election cycle (defined as the four years ending in each election year), instead of one year. Results are reported in Tables C.2 and C.3.

The results point to a clear and precisely estimated negative relationship between the two forms of political organization: even when controlling for industry characteristics, sectors with stronger trade associations seem to resort less to campaign financing, having less total and average contributions. Magnitudes are also relatively large: increasing trade association employment by one standard deviation from the mean decreases the total contribution by approximately 20% of a standard deviation, while the corresponding figure for contribution per firm is 17%. The introduction of import penetration barely changes the results.

Table C.2: Union Capacity vs. Total Campaign Contribution

	(1)	(2)	(3)	(4)
VARIABLES	Total Contribution (log)			
	OLS	IV	OLS	IV
Union Employment (log)	-1.177	-1.310		
	(0.419)***	(0.419)***		
Union Payroll (log)			-0.413	-0.498
			(0.190)**	(0.181)***
Import Penetration (log)		-0.333		-0.353
		(1.392)		(1.404)
Union Employment X Import Penetration		-0.245		
		(2.250)		
Union Payroll X Import Penetration				-0.364
				(1.215)
Observations	334	334	334	334
R-squared	0.074	0.096	0.070	0.089
Number of cnae	88	88	88	88

Robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

We also introduce the campaign financing variables in the regressions described by equations (3-1) and (3-2), in order to assess the differential roles of the two forms of political organization in shaping trade policy. Results are in tables C.4 and C.5; reported specifications include controls from PIA and RAIS, and even-number also include import penetration.

Results support the idea of a substitution between the two modes of political organization: when trade association capacity is controlled for, there seems to be a negative effect of total and average campaign contributions on the prevalence of non-automatic licensing. The coefficients for average donation per firm (Table C.5) are quite precisely estimated, although the magnitudes are relatively small: increasing contribution per firm by one standard deviation from the mean reduces the prevalence index by only 0.7% of a standard deviation.

Table C.3: Union Capacity vs. Average Campaign Contribution

VARIABLES	(1)	(2)	(3)	(4)
	Contribution per Firm (log)			
	OLS	IV	OLS	IV
Union Employment (log)	-1.140	-1.090		
	(0.398)***	(0.400)***		
Union Payroll (log)			-0.397	-0.413
			(0.166)**	(0.162)**
Import Penetration (log)		-1.730		-1.754
		(0.719)**		(0.730)**
Union Employment X Import Penetration		-0.880		
		(0.895)		
Union Payroll X Import Penetration				-0.691
				(0.459)
Observations	334	334	334	334
R-squared	0.092	0.152	0.082	0.143
Number of cnae	88	88	88	88

Robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.4: Union Capacity vs. Campaign Contributions and Licensing

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Non-Automatic Licensing (Prevalence Index)					
	OLS	OLS	IV	OLS	OLS	IV
Union Employment (log)	0.134	0.089	0.090			
	(0.056)**	(0.051)*	(0.052)*			
Union Payroll (log)				0.029	0.016	0.017
				(0.027)	(0.025)	(0.025)
Total Contribution (log)	-0.009	-0.006	-0.006	-0.010	-0.009	-0.009
	(0.004)**	(0.004)	(0.004)	(0.005)**	(0.005)**	(0.005)**
Import Penetration (log)		-0.179	-0.052		-0.238	-0.102
		(0.320)	(0.223)		(0.342)	(0.242)
m penetration # employment		0.906	0.891			
		(0.487)*	(0.484)*			
m penetration # payroll					0.358	0.353
					(0.280)	(0.279)
m penetration # total contribution		-0.031	-0.036		0.001	-0.004
		(0.036)	(0.032)		(0.036)	(0.031)
Observations	332	332	332	332	332	332
R-squared	0.320	0.363		0.299	0.327	
Number of cnae	88	88	88	88	88	88

Robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.5: Union Capacity vs. Campaign Contributions and Licensing

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Non-Automatic Licensing (Prevalence Index)					
	OLS	OLS	IV	OLS	OLS	IV
Union Employment (log)	0.165	0.121	0.123			
	(0.063)**	(0.057)**	(0.058)**			
Union Payroll (log)				0.037	0.024	0.025
				(0.029)	(0.027)	(0.027)
Contribution per firm (log)	-0.017	-0.015	-0.014	-0.020	-0.020	-0.020
	(0.006)***	(0.007)**	(0.007)**	(0.006)***	(0.007)***	(0.006)***
Import Penetration (log)		-0.340	-0.163		-0.338	-0.166
		(0.336)	(0.233)		(0.328)	(0.232)
m penetration # employment		0.795	0.771			
		(0.468)*	(0.469)			
m penetration # payroll					0.316	0.305
					(0.267)	(0.267)
m penetration # contribution per firm		-0.038	-0.049		0.016	0.005
		(0.068)	(0.062)		(0.066)	(0.060)
Observations	332	332	332	332	332	332
R-squared	0.342	0.376		0.311	0.335	
Number of cnae	88	88	88	88	88	88

Robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.3
Robustness – Alternative Variables

Table C.6: Employee Unions: Number of Unionized Employees

	(1)	(2)	(3)
VARIABLES	Non-Automatic Licensing (Prevalence Index)		
	OLS	OLS	IV
Trade Assoc. Employment (log)	0.097	0.220	0.252
	(0.039)**	(0.068)***	(0.082)***
Number of Unionized Employees (log)	0.009	0.003	-0.002
	(0.011)	(0.008)	(0.010)
Import Penetration (log)		-0.043	-0.020
		(0.011)***	(0.016)
Trade Assoc. Employment X Import Penetration		0.022	0.026
		(0.006)***	(0.009)***
Industry Controls	Yes	Yes	Yes
Industry and year FE	Yes	Yes	Yes
Observations	1,309	1,309	1,309
R-squared	0.303	0.356	0.326
Number of cnae	88	88	88

Robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.7: Productivity and Trade Association Employment

	(1)	(2)
	Trade Association Employment (log)	
VARIABLES	Last - First	Avg. Last 4 - Avg First 4
Productivity (log)	-0.223	-0.161
	(0.143)	(0.145)
Observations	84	85
R-squared	0.023	0.017

Robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.8: Productivity and Trade Association Employment - Panel

	(1)			(2)
VARIABLES	Trade Association Employment (log)			
Productivity (log)	-0.257	-0.245		
	(0.141)*	(0.154)		
Productivity (log) (t-1)			-0.288	-0.295
			(0.147)*	(0.162)*
Industry and year FE	Yes	Yes	Yes	Yes
Industry-level controls	No	Yes	No	Yes
Observations	1,372	1,309	1,278	1,215
R-squared	0.055	0.063	0.046	0.056
Number of cnae	88	88	88	88

Robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.9: Productivity, Trade Association Employment and Licensing

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Non-Automatic Licensing (Prevalence Index)					
	OLS	OLS	OLS	OLS	IV	IV
Trade Assoc. Employment (log)	0.095	0.093	0.231	0.222	0.272	0.268
	(0.039)**	(0.037)**	(0.069)***	(0.068)***	(0.080)***	(0.081)***
Productivity	-0.093	-0.094	-0.103	-0.119	-0.140	-0.133
	(0.072)	(0.069)	(0.067)	(0.069)*	(0.073)*	(0.073)*
Import Penetration (log)			-0.041	-0.042	-0.013	-0.019
			(0.009)***	(0.010)***	(0.017)	(0.016)
Trade Assoc. Employment			0.025	0.023	0.030	0.029
X Import Penetration			(0.006)***	(0.006)***	(0.009)***	(0.009)***
Industry Controls	No	Yes	No	Yes	No	Yes
Industry and year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,372	1,323	1,372	1,323	1,372	1,323
R-squared	0.276	0.297	0.344	0.352		
Number of cnae	88	88	88	88	88	88

Robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C.4 Robustness – Results using Trade Association Payroll

Table C.10: Trade Association Payroll and Protection Measures

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Average Tariff		NTMs (Prevalence Index)		Non-Automatic Licensing (Prevalence Index)	
	OLS	OLS	OLS	OLS	OLS	OLS
Trade Assoc. Payroll	0.053	0.197	0.338	0.207	0.023	0.019
	(0.322)	(0.314)	(0.632)	(0.595)	(0.019)	(0.017)
Industry Controls	No	Yes	No	Yes	No	Yes
Industry and year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,372	1,323	1,372	1,323	1,372	1,323
R-squared	0.224	0.264	0.545	0.557	0.258	0.284
Number of cnae	88	88	88	88	88	88

Robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.11: Trade Association Payroll, Import Penetration and Protection Measures

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Average Tariff		NTMs (Prevalence Index)		Non-Automatic Licensing (Prevalence Index)	
	OLS	OLS	OLS	OLS	OLS	OLS
Trade Assoc. Payroll	-0.065	0.117	0.984	0.961	0.083	0.072
	(0.458)	(0.414)	(0.767)	(0.724)	(0.030)***	(0.031)**
Import Penetration (log)	0.057	0.032	-0.372	-0.555	-0.037	-0.039
	(0.151)	(0.120)	(0.200)*	(0.227)**	(0.009)***	(0.011)***
Trade Assoc. Payroll X	-0.021	-0.014	0.116	0.131	0.011	0.009
Import Penetration	(0.040)	(0.035)	(0.057)**	(0.059)**	(0.003)***	(0.003)***
Industry Controls	No	Yes	No	Yes	No	Yes
Industry and year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,372	1,323	1,372	1,323	1,372	1,323
R-squared	0.225	0.264	0.551	0.565	0.302	0.319
Number of cnae	88	88	88	88	88	88

Robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.12: Robustness

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Non-Automatic Licensing (Prevalence Index)					
	OLS	OLS	OLS	OLS	OLS	OLS
Trade Assoc. Payroll	0.021	0.073	0.018	0.072	0.018	0.071
	(0.018)	(0.031)**	(0.017)	(0.031)**	(0.012)	(0.028)**
Trade Assoc. Payroll (t+1)					0.005	-0.005
					(0.010)	(0.013)
Employee Unionization Rate	0.139	0.134				
	(0.080)*	(0.081)				
Share of Nonfinal Goods			-0.129	-0.068		
			(0.101)	(0.112)		
Import Penetration (log)		-0.039		-0.038		-0.031
		(0.011)***		(0.011)***		(0.010)***
Trade Assoc. Payroll X		0.009		0.009		0.009
Import Penetration		(0.003)***		(0.003)***		(0.003)***
Trade Assoc. Payroll X						-0.001
Import Penetration (t+1)						(0.001)
Industry Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry and year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,309	1,309	1,323	1,323	1,230	1,230
R-squared	0.289	0.323	0.286	0.319	0.283	0.308
Number of cnae	88	88	88	88	88	88

Robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.13: Trade Association Payroll, Import Penetration and Protection Measures

VARIABLES	(1)	(2)	(3)	(4)	(5)
	Non-Automatic Licensing (Prevalence Index)				
	IV	IV	IV	IV	IV
Trade Assoc. Payroll	0.274	0.270	0.091	0.079	0.076
	(0.081)***	(0.081)***	(0.047)*	(0.038)**	(0.039)*
Trade Assoc. Payroll (t+1)			-0.017		
			(0.035)		
Employee Unionization Rate				0.149	
				(0.083)*	
Share of Nonfinal Goods					-0.102
					(0.118)
Import Penetration (log)	-0.015	-0.025	-0.005	-0.011	-0.010
	(0.017)	(0.016)	(0.015)	(0.015)	(0.015)
Trade Assoc. Payroll X Import Penetration	0.030	0.029	0.011	0.010	0.010
	(0.009)***	(0.009)***	(0.006)*	(0.004)**	(0.004)**
Trade Assoc. Payroll X Import Penetration (t+1)			-0.002		
			(0.004)		
Industry Controls	No	Yes	Yes	Yes	Yes
Industry and year FE	Yes	Yes	Yes	Yes	Yes
Observations	1,372	1,323	1,230	1,309	1,323
R-squared	0.294	0.326	0.272	0.294	0.290
Number of cnae	88	88	88	88	88

Robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.