Collective Bargaining Networks, Rent-sharing, and the Propagation of Shocks

Santiago Hermo*

Job Market Paper
(Click here for latest version)

October 2, 2023

Abstract

Growing evidence indicates that workers are affected by shocks to the product market demand of their employers, yet the role of labor market institutions in determining the winners and losers of these shocks is not well understood. I study the role of collective bargaining, a prevalent wage-setting institution in many countries, in determining the effect of economic shocks across firms. To do so, I leverage novel administrative data which allows me to construct the network linking employers to collective bargaining agreements in Argentina. I exploit changes in world import demand between 2009 and 2013 to construct exogenous shocks to both the product demand of the individual firm and the average agreement-level product demand. My findings indicate a 1.5% wage increase following a shock equivalent to a 10% rise in firm revenue, and a 4.3% wage increase following a shock equivalent to a 10% rise in average revenue of firms under the same agreement. The evidence suggests that these effects are driven by changes in common wage floors, which means that bargaining extends the impact of economic shocks to firms and workers not directly affected. I develop and estimate a general equilibrium model of the labor market with collective bargaining to study how the degree of centralization of bargaining affects the intensity of shock propagation. Contrary to expectation, I find that counterfactual networks with more centralized bargaining do not necessarily lead to stronger shock propagation.

Keywords: Collective bargaining, Rent-sharing, Wage floors, Trade Shocks, Networks.

*I am indebted to Jesse M. Shapiro, Lorenzo Lagos, Peter Hull, and Neil Thakral for continuous feedback and support throughout the development of this project. I am also indebted to Victoria Castillo, David Trajtemberg, and the staff of the *Dirección General de Estudios y Estadísticas Laborales* at the Ministry of Labor of Argentina, who not only granted access to the administrative data but also provided valuable help in understanding the data and the institutional context. I am thankful to Constanza Abuin, Pedro Dal Bo, Diego Gentile Passaro, Matthew Pecenco, Pascuel Plotkin, and Sara Spaziani, for helpful comments and exchanges. I gratefully acknowledge support from the Orlando Bravo Center for Economic Research at Brown University. E-mail: santiago_hermo@brown.edu

1 Introduction

A robust literature documents that economic shocks to firms or regions affect workers' wages (e.g., Van Reenen 1996; Autor et al. 2013; Hummels et al. 2014; Dix-Carneiro and Kovak 2017). While some studies suggest that collective bargaining (CB) may be a mediator in this relationship (e.g., Rose 1987; Abowd and Lemieux 1993; Gürtzgen 2009b; Rusinek and Rycx 2013), its role is not well-understood. Bargaining enables unions to negotiate provisions for workers, such as wage floors, thus potentially allowing workers to gain from economic shocks that increase average firm profitability. In doing so, bargaining may decouple changes in local profitability from changes in local wages, implying that idiosyncratic shocks will have a weaker impact on workers. Consequently, the composition of CB units—or, in other words, the "CB network"—may determine who benefits from economic shocks. For instance, the response of regional wages to a large regional shock may be different depending on whether those firms are grouped into a single bargaining unit, or whether they belong to a larger unit that includes firms in non-affected regions.

Collective bargaining institutions vary greatly across countries.[1] Consequently, understanding the role of the CB structure in shaping the impact of economic shocks on wages can be important for policy. If shocks affect most firms in a CB unit equally, wages will likely respond strongly. In contrast, if different firms experience disparate shocks, then the response of wages will likely be more muted. The CB network will determine the magnitude of wage responses, and the extent to which the shock is propagated to non-directly affected firms. Countries with more centralized bargaining may thus be more resilient to shocks as they can more easily spread the risk across firms, mitigating the need for protective policies. Sectoral bargaining may also imply that wages are transmitted to non-affected firms, potentially increasing the need for policies to mitigate negative effects. Similarly, in order to mitigate negative effects, trade policies could be designed to avoid concentrating shocks in a few firms.

In this paper, I study how collective bargaining shapes the impact of economic shocks to firms. First, I leverage novel administrative data from Argentina to construct the network linking firms to CB units which, coupled with rich labor market data, allows me to study how shocks propagate through the CB network. I construct product-demand shocks at the firm and CB unit levels exploiting changes in international demand for the products that firms export, and compare the evolution of outcomes for firms in the same province and economic sector that receive different shocks. Additionally, I construct a dataset of wage floors that allows me to study the role of wage floors in the propagation of shocks. Second, I develop and estimate a structural model of local labor markets with CB units that negotiate over wage floors, and use it to study the incidence of shocks under counterfactual bargaining structures. To do so I simulate the exporting shocks in the model, verify that the model replicates the empirical patterns, and explore how the shock propagates once I change the composition of CB units.

[1] As of 2017, collective bargaining existed in the private sector of all 52 Western economies surveyed by Visser (2019). Different levels of bargaining were prevalent: local or company-level in 23 countries, alternating between local and sectoral in 14, sectoral in 15, and alternating between central and sectoral in 1.

The case of Argentina in the aftermath of the Great Recession provides an excellent case study for several reasons. First, collective bargaining is widespread in the country, with 93% of workers covered by some agreement in 2014 (Ministerio de Trabajo, Empleo y Seguridad Social 2023). Like in several other countries, agreements establish minimum working conditions for covered workers and firms, implying that the results may be relevant for other countries as well.[2] Second, due to the legal structure, CB units are not entirely determined by region or industry, resulting in a highly idiosyncratic network that allows credible comparisons to identify the effects of shocks. Finally, the country was exposed to an increase in demand for its exports in the aftermath of the Great Recession, which can be plausibly assumed exogenous to the existing CB network. Additionally, due to the high inflation in the period, nominal wage floors were updated frequently, potentially allowing real wage floors to respond.

Administrative data from Argentine Customs and bilateral international trade flows data from Gaulier and Zignago (2010) allow me to construct exporting shocks. I observe exports from every firm in granular product categories to different countries, and the world import demand (excluding Argentina) from each country-product combination. I define shocks to the product demand of a country-product combination as changes in the import demand from that country-product between 2009–2010 and 2012–2013. Firms are exposed to demand changes via the share of their value exported to that country-product (Hummels et al. 2014). CB units are exposed to firms via employment shares, so I define the exposure to a country-product as the sum across firms of employment shares times the share of firm exports to that country-product. Intuitively, if a CB unit has a large share of workers in firms that export to a particular country-product, then the CB is highly exposed to that country-product. Then, I define firm and CB shocks as the average product-demand shock, weighting by the respective exposure shares. Anecdotal evidence suggests that unions are aware of trade developments, which are sometimes incorporated in trade agreements, or prompt unions to demonstrate against them.[3] As a result, I expect the CB shocks to affect the outcomes of the negotiations between unions and employers.

The exporting shocks suggest a strong average increase in world import demand for Argentine products, but with significant heterogeneity across firms and CB units. To identify the effect of CB shocks I compare the evolution of outcomes for firms in the same province and economic sector that are subject to a similar firm shock but a different CB shock. I proceed analogously to identify effects of firm shocks. The key assumption is that the growth in average import demand in the CB unit affected firm outcomes because of the resulting change in negotiations, and not due to other connections between the firms. Similarly, the growth in import demand affected firm outcomes because of the resulting change in their product demand, and not because firms

[2] See Bhuller et al. (2022) for a recent review of collective bargaining institutions in OECD countries.

[3] Two recent examples. First, in 2017 a cut in tariffs for electronic products affected most firms in the relevant CB unit. Following this shock, an agreement was signed that froze nominal wages for 2 years, implying a strong decline in real wages given the expected inflation rate at the time (La Nación 2017). Second, in 2022 a rumor that the government may cut tariffs on tires resulted in a strong mobilization of the union that represents workers of tire production (La Nación 2022).

with differential growth rates sorted into trending markets. These assumptions can be cast in terms of conditional quasi-random assignment of exporting shocks (changes in log WID), as in recent work by Borusyak et al. (2022b). I conduct several tests that support the validity of the quasi-randomness assumption.

My main estimates using exporting firms reveal that, while log wages increase by 0.0173 following a firm shock (SE=0.0093), a CB shock increases log wages by 0.0482 (SE=0.0183). Complementary evidence using data from a survey of businesses indicates that a 10 percent firm shock increases firm revenue by about 1.1 percent, implying that a shock equivalent to a 10 percent increase in average CB revenue would increase wages by an average of 4.4 percent among covered firms. Collective bargaining allows workers to benefit from economic shocks, while also spreading the shocks to possibly non-shocked firms. Turning to employment, I find a null, albeit noisy, effects of CB shocks, and positive effects of firm shocks.

The evidence suggests that the effects of shocks are mediated by wage floors. To obtain direct evidence on the role of wage floors, I constructed a dataset of floors detecting bunching in the distribution of observed wages. Then, I estimate my models using as outcome the wage floor instead of the actual wage in the firm, finding that wage floors increase by a similar magnitude as wages following a CB shock. Importantly, a wage floor should result in heterogeneous employment responses across firms with different productivity. Heterogeneity analyses reveal negative effect of CB shocks on employment for low-wage firms, consistent with a wage floor is more binding for them. I also find positive employment responses for medium productivity firms, suggesting the presence of monopsony power.

A potential threat to the view that CB matters is that shocks actually propagate through other networks that are correlated with CB units, such as geographic proximity or input-output linkages. Several exercises, however, suggest that the causality runs through the CB network. First, I construct a falsification test that focuses on a subset of firms covered by more than one CB, and construct a demanding specification that compares workers in the same firm but bound by different CB units. If a shock to a firm's primary CB unit reflects spillovers through other networks, then we should not observe unit-specific effects within the firm. Second, I consistently find that wage floors respond to CB shocks but not to firm or sectoral shocks. Third, I find robust estimates to varying controls for connections via local labor markets. Finally, I construct a placebo network and confirm that my empirical design finds null effects of placebo shocks.

In the final part of the paper, I develop a general equilibrium model to investigate how the CB network affects the incidence of shocks on wages. The model assumes the existence of heterogeneous local labor markets affected by wage floors. CB units, defined as partitions of local labor markets, bargain over mandatory wage floors anticipating the response of covered firms. An increase in the wage floor constrains more firms at the lower end of the productivity distribution, offsetting monopsony power and increasing employment (and the wage bill) at first. After a threshold, however, the wage floor destroys employment. This hump-shaped response of employment is analogous to the response of regional employment to the minimum wage discussed by Ahlfeldt et al. (2022). I use a "Nash-in-Nash" solution concept, first introduced by Horn and Wolinsky (1988), to model the equilibrium of the bargaining game between unions and employer associations. The key parameters that govern heterogeneity in the model are estimated by inversion of equilibrium conditions. In particular, I use the share of firms bunching at the wage floor to obtain an unobserved productivity parameter in each local labor market. Similarly, I invert first order conditions of the Nash bargaining problem to obtain bargaining power parameters of unions. I simulate the exporting shocks in the model, and verify that the model is able to replicate the empirical patterns in the data.

The model allows me to assess the role of the CB network in the propagation of shocks. I manipulate the existing CB network to generate counterfactual bargaining structures that vary in the size of CB units, a proxy for the degree of centralization of bargaining. I simulate the effect of shocks under these counterfactual CB networks, and compute the correlation between local shocks and local wage changes as a measure of shock propagation. Contrary to expectation, I find that more centralized bargaining not always results in more shock propagation. Highly decentralized or highly centralized bargaining structures result in a strong correlation between shocks and wage changes, while intermediate structures result in a weaker correlation. The reason is that the model imposes a unique wage floor for all firms in a CB unit, and networks with centralized bargaining endogenously result in less binding wage floors. As a result, both highly decentralized and highly centralized bargaining structures results in a strong pass-through of local shocks to wages.

This article contributes to several strands of literature. First, the paper shows clean evidence of "collective rent-sharing": wages increase in CB units that are exogenously exposed to positive shocks. Rose (1987) and Abowd and Lemieux (1993) also find wage responses to CB shocks, the former in a deregulation episode in the US trucking industry, and the latter in the response of contract wages to international prices in the context of Canadian manufacturing. More recent work relying on administrative data (e.g., Gürtzgen 2009b; Rusinek and Rycx 2013) finds that wages are more responsive to firm shocks when bargaining is decentralized. Card and Cardoso (2022) find that growth in wage floors is associated to the central tendency of productivity growth in covered firms.[4] Garin and Silvério (2023) use exporting shocks in Portugal and find that their effects depend on whether they are idiosyncratic to a firm or common to a market. My contribution is to isolate the role of CB shocks across multiple industries using quasi-random product demand shocks, controlling for changes in demand at the firm level. Additionally, my estimates reconcile the divergent rent-sharing elasticities found in studies relying on micro-data and those from macro calibrations (Jäger et al. 2020).

Second, the paper shows that the effects of trade shocks are mediated by labor market institutions, pointing towards a novel channel for the regional contagion of shocks. This finding contributes to our understanding of the spatial effects of economic shocks, such as those arising from international trade (e.g., Topalova 2010; Autor et al. 2013; Dix-Carneiro and Kovak 2017).

[4] Bhuller et al. (2022) performs a similar analysis for the case of Norway.

Adão et al. (2022) study the role of spatial linkages in the propagation of shocks, and Felix (2022) discusses the role of local labor market concentration. Borusyak et al. (2022a) points out that the effects of regional shocks on migration depend on a region's shock and on the shocks of connected regions as well. Boeri et al. (2021) argue that centralized bargaining leads to employment misallocation, suggesting welfare gains from decentralization. My findings suggest that decentralization may also lead to more volatile wages, which may be undesirable from a welfare perspective.

To my knowledge, this is the first paper to incorporate bargaining and endogenous wage floors in a spatial economic model, allowing for varying degrees of centralization in bargaining.[5] While in my model negotiations are simultaneous, following the "Nash-in-Nash" literature (Collard-Wexler et al. 2019), the method can be adjusted to better suit other bargaining systems as well. Similar to Ahlfeldt et al. (2022) and others (e.g., Parente 2022), I model the impact of wage floors on employment assuming heterogeneous firms that face a minimum wage constraint.

More broadly, the paper relates to a long literature studying unions and collective bargaining (e.g., Freeman and Medoff 1984; Card 1990, 1996). In particular, several papers have studied the properties of different bargaining regimes both theoretically and empirically (Calmfors and Driffill 1988; Holden 1988; Cardoso and Portugal 2005; Plasman et al. 2007; Boeri et al. 2021). Bhuller et al. (2022) calls for "closing the gap between how economists tend to model wage setting and how wages are actually set." This paper takes a step in that direction by modeling the institutional structure of collective bargaining explicitly, and using an estimated model to evaluate the effects of different bargaining structures in a principled way.

The paper is organized as follows. Section 2 presents a simple theoretical framework. Section 3 describes the context and data, Section 4 discusses the empirical strategy used to estimate the effects of shocks, and Section 5 dives into the results. I present a structural model of the labor market with collective bargaining in Section 6, discuss its estimation and validation in Section 7, and use it to conduct counterfactual exercises in Section 8. Section 9 concludes.

2 Theoretical Framework

In this section, I discuss a motivating theoretical framework that with heterogeneous firms under a collective bargaining process to determine the likely response to effects in wage floors. This will help the interpretation of the empirical results, and will be a useful introduction to some elements that will be used in the structural model of Section 6.

2.1 Set-up

I discuss a Nash bargaining problem where a set $\mathcal{J}$ of firms belonging to a CB unit face a wage floor constraint to their wage decision, $w_j > \underline{w}$. The timing is as follows. First, wage floors $\underline{w}_c$

[5] Several articles present theoretical models to study the role of bargaining. For example, Corneo (1995) and Naylor (1998) study how the bargaining structure affects the response of national labor markets to trade integration. Davidson (1988) shows that industry-level bargaining leads to higher wages in oligopolistic industries.

are determined in Nash-bargaining in CBA c. Unions and employers anticipate the response of covered firms when negotiating. Second, firms with productivity φ_j choose wages and employment given the wage floor.

2.2 Firm problem

A finite set of firms $j \in \mathcal{J}$ faces an upward-sloping labor supply curve $\ell_j(w)$ at wage w. The production function is $y_j = \varphi_j f(\ell_j)$, so firms are heterogeneous in productivity φ_j. A wage floor $\underline{w}_c$ sets a minimum to the wage that firms can pay, where c is the collective bargaining unit. The firm's static decision problem is thus given by

$$w_j^* = \arg\max_w \left\{ \varphi_j f(\ell_j) - w\ell_j \;\middle|\; \ell_j = \ell(w),\; w \geq \underline{w}_c. \right\}$$

The solution is characterized by two thresholds that determine firms' behavior given their productivity. This result, proven in more detail by Ahlfeldt et al. (2022), is used here to discuss the effects of shocks at the collective bargaining level. I will be more explicit in deriving this result in the structural model of Section 6.

Firms with $\varphi_j > \overline{\varphi}$ are *unconstrained* by the wage floor. Since they optimally choose wages above the floor, we can write $w_j^* = w_j(\varphi_j)$ and $\ell_j^* = \ell_j(w_j)$. The unconstrained wage exhibits a wage markdown over the marginal product of labor, as in monopsonistic labor markets (Manning 2011; Card et al. 2018). Given the wage-posting nature of the model, increases in productivity lead these firms to hire more workers at higher wages (Oi and Idson 1999).

Firms with $\varphi_j \leq \overline{\varphi}$ are *constrained* by the wage floor, so that $w_j^* = \underline{w}_c$ and $\ell_j^* = \ell_j(\underline{w}_c, \varphi_j)$ for them. When $\varphi_j \leq \underline{\varphi}$ as well we have $d\ell_j(\underline{w}_c, \varphi_j)/d\underline{w} < 0$, i.e., these firms lower employment when $\underline{w}_c$ increases. They do so because, at their monopsony equilibrium, the marginal product of labor (MPL) equates the marginal cost of labor (MCL) at a level lower than $\underline{w}_c$. Thus, as the MCL increases to $\underline{w}_c$, these firms need increase the MPL to equate it to $\underline{w}_c$, which they achieve by reducing employment. These firms may also close down if not profitable, resulting in employment losses as well. If $\varphi_j \in (\underline{\varphi}, \overline{\varphi})$ firms are constrained as well, but they respond to the wage floor by increasing employment. At their monopsony equilibrium, the equality between the MPL and the MCL is achieved at a level higher than the wage floor. When the MCL increases to $\underline{w}_c$, these firms want to lower the MPL, which they do by increasing employment. By reducing the monopsony power, the wage floor increases employment for this group of firms.

As discussed by Ahlfeldt et al. (2022, Proposition 1), in this setting aggregate employment is hump-shaped in the wage $\underline{w}$, so the employment-maximizing wage floor is binding.

2.3 Nash bargaining with heterogeneous firms

Within a CB unit we can define aggregate revenue $R(\underline{w}) = \sum_{j\in\mathcal{J}} \varphi_j f(\ell_j)$ and the aggregate wage bill $WB(\underline{w}) = \sum_{j\in\mathcal{J}} w_j \ell_j$. I assume that the objective of the union is to maximize the wage bill, so that $U(\underline{w}) = WB_c(\underline{w})$, and that the objective of the employers is to maximize aggregate profits, so that $\Pi(\underline{w}) = R(\underline{w}) - WB(\underline{w})$. We assume that, in case of a floor $\underline{w}'$ that is not binding, aggregate profits are positive ($R(\underline{w}') > WB(\underline{w}')$). I discuss this functional forms in Section 6.2.3. Letting $\beta \in (0,1)$ be the bargaining power of the union, the Nash bargaining problem is

$$\max_{\underline{w}} U\left(\underline{w}\right)^{\beta} \Pi\left(\underline{w}\right)^{1-\beta}. \tag{1}$$

The optimal wage floor is implicitly defined by

$$WB(\underline{w}^*) = \omega R(\underline{w}^*) \tag{2}$$

where $\omega \in (0,1)$ is a weight given by

$$\omega = \frac{\beta}{\beta + (1-\beta)\left(-\frac{d\Pi}{d\underline{w}} / \frac{dU}{d\underline{w}}\right)}. \tag{3}$$

If $\beta = 1$ then the problem amounts to selecting the wage bill-maximizing wage floor. If $\beta = 0$ then the selected wage floor will be non-binding, as this is the profit-maximizing solution.

The solution sets the wage floor so that the wage bill equals a fraction of aggregate revenue. If we divide (2) by total employment, and add an outside option for workers in the definition of U, then we would get the familiar result that average wages are a weighted average of revenue per worker and the outside option. We see that the solution is analogous to the classical Nash bargaining problem in which unions set wages instead of wage floors. The main difference is in the weight ω, which may differ from β. For instance, if the wage floor is more "painful" for firms relative to how "beneficial" it is for unions ($-d\Pi/d\underline{w} > dU/d\underline{w}$), then ω will be smaller.

Proposition 1 (Response of wage floor)**.** *Assume a change in the productivity profile $\{d\ln\varphi_j\}$ such that, to a first approximation, ω is fixed. Then, we can write the change in the wage floor as*

$$d\ln\underline{w} = \frac{WB}{\tilde{WB}^{\text{co}}}\left[\sum_{j\in\mathcal{J}} s_j^R d\ln\varphi_j - (1-\omega)\sum_{j\in\mathcal{J}} \iota_j s_j^{WB} d\ln\varphi_j\right] \tag{4}$$

where $s_j^R = R_j/R_c$ is the share of revenue of firm j in the CBA, $s_j^{WB} = WB_j/WB_c$ is the analogous share for the wage bill, $\tilde{WB}_c^{\text{co}}$ is the wage bill of constrained firms adjusted for its response to the wage floor, and ι_j is the elasticity of the wage bill to productivity φ_j. Allowing ω to change results in a third term in the expression that depends on the responses in the ratio $(-d\Pi/d\underline{w})/(dU/d\underline{w})$ to the changes in productivity and the wage floor.

The proof is available in Appendix A. Proposition 1 shows that $\underline{w}$ responds to a weighted average of changes in log productivity minus a weighted average of wage bill elasticities times changes in log productivity.[6] The adjustment term reflects the fact that firms respond to the

[6] Card and Cardoso (2022) study Portuguese CB and find that the best predictor of the change in wage floors is

shock changing wages in proportion to revenue, yet revenue is down-weighted in the Nash split, so the wage bill increases "in excess." If the shocks already increase the wage bill significantly, then $\underline{w}_c$ needs to increase by less to restore equilibrium.

We also note that the response of $\underline{w}_c$ to productivity shocks is decreasing in the adjusted constrained wage bill $\tilde{WB}_c^{\text{co}}$.[7] The reason is that, if the adjusted wage bill is large, then the shock is already inducing firms to increase wages, so the wage floor needs to increase by less. Interestingly, $\tilde{WB}_c^{\text{co}}$ is decreasing in the union bargaining power β. As a result, stronger unions will result in larger responses of wage floors to productivity shocks.

If ω is allowed to vary then the response of $\underline{w}_c$ will also depend on a third term that depends on the sum of the responses of $(-d\Pi/d\underline{w})/(dU/d\underline{w})$ to the changes in productivity in each firm and the wage floor. Because we expect the responses to the wage floor and to productivity changes to have opposite signs, they are likely to cancel out justifying the approximation of a fixed ω.

2.4 Predictions for firms following a CB shock

Consider a shock that increases average productivity, so that the wage floor goes up, and to make things concrete focus on a firm for which $d\varphi_j = 0$. This firm will respond to the wage floor by either decreasing employment, if its productivity is below the lower threshold $\underline{\varphi}$, or by increasing employment, if its productivity is between $\underline{\varphi}$ and $\overline{\varphi}$. In both cases, the firm will increase wages. Now, if its productivity is above $\overline{\varphi}$, then the firm will not be affected by the wage floor.

In the empirical analysis I will test for these predictions by exploring the response of firms to a CB shock conditional on the firm shock, and in particular by testing for heterogeneous responses of firms with different productivity levels.

3 Context and Data

In this section, I describe labor market institutions in Argentina, the economic context of the period under study, and the data that I use in the empirical analysis. I provide a concise description focusing on features relevant for this article, and refer to the appendix for details.

3.1 Labor market institutions in Argentina

The formal labor market in Argentina operates within a complex regulatory framework. The law sets general standards for all labor relations, and a set of collective bargaining agreements (CBAs) establishes standards that are binding for different subgroups of workers. The law stipulates that individual employers cannot modify the terms of the CBAs to the detriment of workers, but can improve upon them. Consequently, CBAs establish minimum standards for covered workers.

---

the (unweighted) mean change in value added, with the median as a second close. The authors find that the 10th, 25th, 75th, and 90th percentiles, show much lower predictive power.

[7] See (A.2) in the Appendix for an exact expression for $\tilde{WB}_c^{\text{co}}$.

Only a subset of existing unions can negotiate CBAs. Based on certain prerequisites, the government grants bargaining privileges to a single union per "area of representation," specified by industry, occupation, geographical location, or a single employer. Typically, the union with privileges was assigned historically by the national government. As a result, the structure of the collective bargaining network has been stable in the study period, especially in mature sectors that are exposed to international trade.

Importantly, the definition of areas of representation is based on verbal descriptions and is not exact. As an example, Appendix Table 1 shows the description for three CBAs in the textile industry.[8] Consequently, workers in observably similar firms in terms of their economic activity and region may fall under different CBAs. Additionally, the law allows a single firm to have employees under multiple CBAs, a scenario that applies to around 16% of private sector firms. For my main empirical analysis I assign a "primary CBA" to each firm, although I use firms that have workers in multiple CBAs for a falsification exercise.

When talking about CBAs I was referring to the comprehensive contracts that define a CB unit. The government archives these "master CBAs" under unique codes, which I observe in the data. A master CBA may be modified by a new master CBA that supersedes it,or a "CBA alteration" that simply updates some provisions within it.[9] CBA alterations act as amendments to the master CBA, and typically refer to updates in wage scales.

Coverage of CBAs is nearly universal, with exceptions only for managerial roles and certain professions. This is so because the law establishes "universal coverage," meaning that CBAs are automatically extended to workers not affiliated with the union, and "automatic extension," meaning that CBAs are automatically extended to all firms in the area of representation. In 2014, of a total 6.4 million formal workers, 80% were covered by CBAs under the main private sector bargaining regime, 7% were not covered by any CBA, and the remaining workers were under special regimes (Ministerio de Trabajo, Empleo y Seguridad Social 2023).

Appendix B.1 provides more details on labor market institutions in Argentina.

3.2 The socio-economic context

Figure 1 shows the trajectory of the Argentinian economy in the years 2004–2019. Panel (a) shows the evolution of GDP, Panel (b) shows the inflation rate, and Panel (c) the evolution of exports by broad category. Coming out of a crisis in 2002, the economy experienced recovery and rapid growth with relatively low inflation. While the Great Recession affected growth in 2009, the economy remained strong for a few more years. However, the economy started to slow down, and by 2015 real GDP had been stagnated for 4 years and annual inflation rates had risen above 30%. Despite a change in the ruling party in December 2015, the economy continued to deteriorate and

[8]From these descriptions, a firm that declares as economic activity some subgroup of textile manufacturing may be covered by any of the three CBAs. For instance, CBAs 0500/07 and 0746/17 both specify coverage for mattress-making activities.

[9]Master CBAs cannot expire. This feature, known as "ultra-activity," is common in many countries.

even fell into the COVID pandemic.

The post-Great Recession growth during 2010-2012 was partly driven by an ongoing surge in international demand for Argentinian products. Although this demand receded slightly, it cannot fully explain the steep decline in exports in 2014-2015. I leverage heterogeneity of this demand increase across destination countries and detailed products to construct my identification strategy.

Appendix Figure 1 shows the dynamics of collective negotiations in 2005–2019. A change in the political landscape after the 2002 crisis revitalized negotiations (Palomino and Trajtemberg 2006), resulting in new master CBAs as shown in Panel (a). Since 2007 soaring inflation prompted unions and employers to meet nearly annually to revise wages via CBA alterations. Panel (b) shows a large increase in alterations that persisted throughout the period. Panel (c) shows that the share of CBA alterations that mention wage issues increased by 25% between 2009 and 2018.

The fact that negotiations to revise wages are frequent in the study period turns out to be a feature of the empirical context, as *real* wage floors can potentially be affected significantly in response to changes in the economic environment faced by firms within the bargaining unit.

3.3 Data

The first administrative dataset I use is a matched employer-employee dataset maintained by the Ministry of Labor, covering the years 2007 through 2020. The key variable of interest is total monthly compensation for each worker-firm relationship. The data also include the worker's hiring modality for the job, their gender and age, as well as the firm's fiscal location (postal code) and a 6-digit economic sector, which is defined using a custom version of ISIC codes, version 4.[10] Importantly, the data does not include information on hours or full-time status. Second, I use data from *Simplificación Registral*, a national system that was introduced in 2008. The dataset contains information at worker hiring and termination dates, and includes the CBA code, the worker's category within the CBA, and an occupation code. I join these data to the matched employer-employee dataset using firm and worker identifiers. See Appendix B.2 for details.

I use two additional data sources. First, I construct exporting shocks relying on administrative data from Argentinian Customs for 2011–2020, and international trade flows data from BACI-CEPII (Gaulier and Zignago 2010) for 2007–2020. I harmonize product codes in the Customs data to 6-digit Harmonized System codes to match the datasets. Second, I use a survey of firms to study the effect of shocks on firm revenue and expenditures. See Appendix B.3 for details.

Due to the gradual implementation of *Simplificación Registral* the CBA code is not observed for many labor relations. I take several steps to impute this variable for workers with missing values, which increases coverage from 70% to 85% after 2011 for private sector workers. I also updated the CBA codes to the latest version so that they represent a constant CB unit. Upon cleaning the worker-level CBA code variable, I designate a "primary CBA" to each firm. All firms in the economy are assigned a primary CBA code. See Appendix B.4 for details.

[10] A firm's fiscal postal code may not coincide with its production site. However, fiscal provinces are likely to coincide, which is why I use this geography in my empirical analysis.

Heterogeneity in CBA coverage. I use a firm's primary CBA to explore the structure of the CB network. The median CB unit spans across 3 provinces and 4 economic sectors (4-digit, ISIC). The 25th and 75th percentiles are 1 and 8 provinces, and 2 and 11 sectors. The most prevalent CBA, which covers retail workers, is present in all 24 provinces and 262 out of 295 4-digit economic sectors. The CB network exhibits substantial heterogeneity in terms of the sectors and regions that it covers, with many cases of CBAs within the same sector and region.

Appendix Figure 3 illustrates this heterogeneity showing the proportion of firms in each CBA that appears in a set of textile-related economic sectors, and the proportion of firms in different sectors covered by three textile CBAs. We note that all sectors contain firms under multiple CBAs, and the presence of these CBAs varies across sectors. Additionally, individual CBAs often encompass multiple sectors. Appendix Figure 4 presents the economic sectors covered by two of the largest CBAs in the economy, which extend across hundreds of sectors.

Estimating wage floors. The administrative data provides a CBA code and a code for the worker's occupation category within the CBA. However, it does not include the wage floors for different worker categories.[11] I estimate wage floors by detecting bunching in the distribution of wages within CBAs, worker categories, CBA-regions, and month cells. Then, I use the time variation in the estimated wage floors to, first, drop CBAs that present highly volatile estimates, and second, to smooth the estimated wage floors so that the percent difference across categories is constant over time, and all categories experience the same time trend. For validation, I compare the estimated wage floors with a sample of manually collected wage floors. Appendix C discusses the details of this procedure.

A yearly panel of firms. For my main analysis, I create a panel dataset at the firm-year level for the period 2007–2017, and for 2011–2017 for wage floors. To do so, I first deflate nominal wages and wage floors by the consumer price index (CPI), and compute mean monthly wages and wage floors for each labor relation within each year. Next, I compute the average real monthly wage and wage floor and tally the number of workers in each firm-year. I also compute the share of workers in the main hiring modality, which is a good proxy for the share of permanent full-time workers.I observe a firm's 6-digit sector and a firm's province, and I add information from survey data on firm revenue and expenditures for years 2010–2012 and 2014–2016. I detail the construction of the exporting shocks and the baseline analysis sample in the next section.

4 Empirical Strategy

In this section I present the empirical strategy used to study the propagation of economic shocks through collective bargaining. The strategy leverages fluctuations in world import demand for

[11] A dataset containing wage floors is not readily available. Acquiring this information typically requires reviewing the text of CBAs, usually available in scanned PDF format, making manual collection of wage floors impractical.

granular products to construct firm- and CB-level shocks. Then, I use these shocks in a difference-in-differences strategy. I discuss the identification assumptions and present falsification exercises that test the validity of the results.

4.1 The ideal experiment

The ideal experiment would consist of randomly changing the demand for different granular products produced by firms in order to obtain exogenous variation at two distinct levels: the firm's product demand, and the average of firm's product demands within each CB unit. As yearly negotiations unfold over time and incorporate changes in the profitability conditions of firms, this type of variation would allow me to study how shocks to firms affect labor market outcomes and whether they propagate through the CB network.

To approximate this ideal, I exploit variation in world import demand (WID) arising from country-product pairs to which firms are exposed. The idea is that, as developing trade relationships is costly, exposure to country-products is fixed in the short-run. As a result, changes in demand from a country-product should increase the sales of firms exposed to them in a plausibly exogenous manner. Similarly, CB units are exposed to changes in WID if they have a large share of employment in firms that are exposed to a country-product. As exporting firms are quite stable over time, exposure of CB units to country-products should also be relatively fixed in the short-run. Variation in WID across country-products would then affect both firms and CB units via their exposure shares.

There are two concerns with this strategy. First, shocks arising from international trade may spill over to other firms through other channels beyond the CB network, such as general equilibrium effects in local labor markets. Second, the shocks may be correlated with other shocks that affect firms in the network, maybe arising from local demand. I leverage the heterogeneity in the CB network to compare firms that are located in the same local labor market but belong to different CB units, controlling for local labor market effects. I use heterogeneity analyses and construct falsification exercises to rule out alternative explanations.

4.2 Identifying trade shocks

Building on the shift-share literature (Borusyak et al. 2022b), I use variation in international demand for country-products exported by Argentine firms interacted with exposure shares to construct shocks at the firm and CB levels. Let WID_{pt} denote the world import demand of country-product $p \in \mathcal{P}$ from the world (excluding Argentina) in year t, where $\mathcal{P}$ is the set of country products. The product-demand shock is defined as

$$f_p = \frac{1}{2} \sum_{t=2012}^{2013} \ln WID_{pt} - \frac{1}{2} \sum_{t=2009}^{2010} \ln WID_{pt}.$$

For each exporting firm j, I then define the firm shock as

$$z_j = \sum_{p \in \mathcal{P}} s_{jp} f_p,$$

where $s_{jp} = EX_{pj} / \left(\sum_{p' \in \mathcal{P}} EX_{p'j} \right)$ and EX_{pj} is the sum of the value exported to country-product p in 2011 and 2012. Section 2 suggests that changes in the negotiated wage floor are determined by the average revenue change across firms in a CB unit, weighted by revenue shares. Since revenue data are not available, I use employment shares $s_{cj} = L^{EX}_{cj} / \left(\sum_{j' \in \mathcal{J}} L^{EX}_{cj'} \right)$, where L^{EX}_{cj} is the number of workers in exporting firm j in CB unit c. Then, for each CB unit c, I define the shock as

$$z_c = \sum_{j \in \mathcal{J}} s_{cj} z_j = \sum_{p \in \mathcal{P}} s_{cp} f_p.$$

Exposure shares are then given by $s_{cp} = \sum_j s_{cj} s_{jp}$, which denotes the contribution of p to c's shock. Note that both exposure shares for firms and CB units sum to one. Shocks are not defined for CB units without exporting firms, which are excluded from the empirical analysis. Appendix Figure 5 shows the distribution of both z_j and z_c. The distribution of the firm shock is bell-shaped, with roughly the same number of firms above and below a positive mean. In comparison, we observe slightly more variation in the CB shocks, suggesting that some CBAs more strongly weight firms with large shocks.

More generally, one can define time-varying versions of the shocks using the change in WID relative to a given year. Figure 2 visualizes the average time evolution of the shocks for different levels of z_j and z_c, relative to 2009. Panel (a) presents the firm shocks, and Panel (b) the CB shocks. We observe stable trends that start to diverge around 2010 and stabilize around 2012–2013. There is a mild decline after 2015, though it is smaller than the preceding increase, suggesting a persistent shock.

These patterns are consistent with an exogenous event that shifted demand for different products, translating into heterogeneous changes in product demand for firms in Argentina that affected CB units differentially. I discuss the validity of this interpretation in the next section.

4.3 A difference-in-differences strategy

Let $I\{\cdot\}$ be an indicator function. The estimating equation for a static difference-in-differences (DiD) model is

$$y_{jt} = \theta z_{c(j)} I\{t \geq 2012\} + \lambda z_j I\{t \geq 2012\} + \alpha_j + \delta_{\ell(j)t} + X'_j \psi_t + \varepsilon_{jt}, \tag{5}$$

where y_{jt} is firm j's outcome in year t, ℓ's are local labor markets so $\delta_{\ell(j)t}$ is an ℓ-specific year fixed effect, X_j is a vector of firm characteristics, and ε_{jt} is an error term. As baseline, I define local labor markets as the interaction between provinces and 4-digit ISIC sectors, though I vary this definition in robustness checks. I include interactions between baseline firm size dummies and 2-digit sector dummies in X_j, as well as with the baseline share of workers in the main hiring modality. I show that the results are robust to different sets of controls. The parameters of interest are λ and θ, and can be interpreted as the effect of an increase in the "dose" of each treatment on the evolution of y_{jt}. I study the effect of the firm shock on revenue in a survey sample to interpret the magnitude of these effects.

To study treatment-effect dynamics I use a specification analogous to (5) that includes interactions of year dummies with the shocks, normalized with respect to 2011. Specifically,

$$y_{jt} = \sum_{s \in \mathcal{S}} \theta_s z_{c(j)} I\{t = s\} + \sum_{s \in \mathcal{S}} \lambda_s z_j I\{t = s\} + \alpha_j + \delta_{\ell(j)t} + X_j' \psi_t + \varepsilon_{jt},$$

where $\mathcal{S}$ is the set of years from 2007 to 2017, excluding 2010 (or 2011 for wage floors).

Econometric identification of these models requires independent variation in each shock, conditional on the other. Appendix Figure 6 plots the firm shock versus the CB shock for each firm. Panel (a) focuses on the raw data, and Panel (b) shows the same plot after residualizing on 4-digit sector and province fixed effects, my baseline definition of local labor markets. There is a small positive correlation in the raw data, which is removed after controlling for local labor market effects.[12] We note significant independent variation in each of the shocks.

Throughout the paper, I cluster standard errors at the CB level for the CB shock z_c and at the firm level for the firm shock z_j.

Identification. Borusyak et al. (2022b) demonstrate that shift-share regressions can be cast in terms of dual regressions at the level of the shifting variable, in our case world import demand at each country-product, and prove that the identification assumption of conditional quasi-random assignment in that dual model is sufficient for causal identification of the treatment effect.[13] Appendix D formally develops the identification argument from Borusyak et al. (2022b) in my setting, and extends it to a scenario with two shift-share variables.

In the context of this paper, this amounts to the assumption that changes in world import demand for each country-product p are uncorrelated with average firm-level unobservables when weighted by the importance of firms in each p. This assumption would be violated if, for example, firms in positively shocked CB units are concentrated in regions with booming local labor markets that affect wages for other reasons. Is the assumption of quasi-random assignment of shocks plausible? Figure 2 suggests somewhat stable trends in the period before 2010, followed by a sharp increase until 2013, suggestive of a large exogenous shock. I explore this view by investigating the correlation of the firm and CB shocks with pre-period characteristics.

[12] The correlation is slightly stronger when we focus on larger firms, as one may expect. However, this difference is also removed after conditioning on local labor market effects.

[13] A condition for this interpretation to hold is that the shares in the definition of the shift-share variables sum to 1. By construction, this holds for both z_j and z_c. Borusyak et al. (2022b) warn that exposure shares that do not sum to one may lead to confounded identification.

Appendix Figure 7 shows estimates of a regression at the firm level of the firm shock on the CB shock, and pre-period firm characteristics (from the period 2007–2009). Using all firms, I find no significant correlation with the CB shock, the pre-period CB shock, and the pre-period wage level, and a small negative correlation with the pre-period share of workers in the main hiring modality. While these observations support the assumption of quasi-randomness, we find significant correlations with the pre-period firm shock and the pre-period firm size. Appendix Figure 8 shows that the apparent auto-correlation in the firm shock is mainly driven by mean reversion at the tails of the distribution, in particular the left tail.[14] To deal with this I construct a baseline sample dropping firms that received extreme values of the firm shock, and I include size controls in my DiD models. Appendix Figure 7 shows that the correlation of the firm shock with the pre-period firm shock and firm size become insignificant after dropping these firms and controlling for firm size.

Appendix Figure 9 explores the correlation of the CB shocks with CB observables. There is no significant correlation with the pre-period CB shock, the number of firms in the CBA, and the share of employment in exporting firms. This supports the view that CB shocks are plausibly exogenous as well.

The assumption that shocks are quasi-randomly assigned implies that the shocks should not affect outcomes in the pre-period. I test whether this is the case by testing for pre-trends, comparing outcomes for firms that received a similar shock prior to the occurrence of the shock.

Baseline sample. I define my "baseline sample" out of the sample of exporters as follows. I keep firms that had an average of 1 to 500 workers in 2007–2009, were operational in 2007 and 2009, and exported between the 1st and 99th percentiles in 2011–2012.[15] I do so to drop outliers and focus on firms that are likely to be affected by the shock. Motivated by the previous discussion, I drop firms that received a pre-period shock in the bottom 5% or top 2% of the distribution. I also exclude firms in CB units with less than 30 firms in total, and a few CB units that had extreme values in the pre-period. I explore the robustness of the results to these restrictions. Appendix Table 3 shows cross-sectional statistics. The sample contains $7,603$ firms, spanning 221 4-digit and 462 6-digit sectors. In the pre-period the average firm has 46.16 employees, and 23.36 percent of firms have less than 10 workers. Appendix Table 4 shows cross-sectional statistics of the 152 CBAs that cover these firms. The average CB unit has 50 exporting firms. Lastly, Appendix Table 5 shows statistics of the main panel of firms used for estimation, spanning from 2007 to 2017. I construct two additional panels used in complementary analyses: one that includes all firms in these exporting CBAs, and a second one at the worker level for workers observed continuously in exporting firms.

[14] Using similar data for Portugal, Garin and Silvério (2023, Figure A.4) also finds evidence of mean reversion at the left of the distribution of exporting shocks.

[15] Out of the total sample of $9,764$ exporting firms in 2011–2012, 0.81 percent have less than 99 percent of their exporting value matched to a world import demand. I drop these firms from the analysis, which after accounting for other restrictions results in 1 extra firm dropped in the baseline sample.

Panel event-study. Appendix E presents a panel event-study design following Freyaldenhoven et al. (forthcoming). While the DiD stands out due to its clarity and simplicity, this alternative approach, used in complementary analyses, has two advantages. First, unlike the DiD model that assumes a single shock between 2009 and 2013, the panel event-study exploits all variation generated by a time-varying version of the shocks. This may be useful if the change in WID for particular firms or CBAs does not line up exactly with the timing assumed in the DiD model. Second, the panel event-study estimates pre-period coefficients by asking whether future shocks are correlated with current outcomes. This means that data from the pre-period is not needed, enabling me to build pre-trends for outcomes that are not observed in 2007–2010.

4.4 Robustness, heterogeneity, and falsification exercises

I conduct several additional exercises to test for potential threats to the empirical strategy and the interpretation of the results.

Heterogeneity by pre-period wages. A threat to the interpretation that CBA negotiations are responsible for observed CB effects is that these are actually driven by unobserved shocks to product-demand that are correlated with CB shocks, such as a concurrent increases in local demand. If this is the case, then a positive CB shock should increase both wages and employment across different types of firms. However, as discussed in Section 2.4, a positive CB shock should affect low-productivity firms, which are constrained by the wage floor, by increasing their wages and reducing employment. Firms with higher productivity should not respond by reducing employment.

To separate these hypotheses I explore the response to CB shocks of firms with different productivity levels. To do so, I employ the static DiD model in (5), but I interact the treatment variables with a proxy for firm productivity. In particular, I construct quartiles of the distribution of average wages in 2007–2009 within each CBA by province cell. I interact my local labor market effects with quartile indicators, thus estimating the effect of a CB shock on wages comparing firms with similar pre-period level of wages.

Worker-level analysis. If the CB shock actually operates through the CB network and not other potentially correlated networks that connect firms, then we should observe that employees under a CB agreement different from the primary one are less affected. Furthermore, these workers should respond to shocks to their own CB unit. However, if the primary CB unit at the firm is a proxy for other networks, then we should not observe CB-specific effects within the firm.

I conduct a worker-level analysis to test whether worker's wages respond to shocks to their own CB unit. To abstract from the extensive margin, I focus on a sample of workers that are employed in the same exporting firm in 2008, 2011, and 2014 and have a non-missing CB agreement code. First, I employ a DiD model with firm by year fixed effects and a CB shock to the worker's own CB unit, instead of the primary CB unit of the firm, as main treatment of interest. This demanding model controls for time-varying unobserved shocks at the firm level, accounting for the possibility that shocks propagate through other networks. Second, I run a separate model using the primary CB shock to the firm and interacting it with an indicator for whether the worker is declared under the primary CBA in the firm. I expect primary CBA workers to be responsible for the effects of primary CB shocks.

Local labor market effects. I estimate the DiD model in equation (5) using different approaches to control for local labor market trends. While the baseline specification uses province by 4-digit sector to define local labor markets, I present results for two alternatives. First, I estimate the same model but defining local labor markets as province by 6-digit economic sector. Second, I define local labor markets with province by 2-digit sector and also control for an exporting shock at the 6-digit sector directly, computed analogously to the CB shock.

Placebo network. I assess the validity of the DiD strategy by constructing a placebo network and estimating the firm-level DiD model using placebo CB shocks. To construct the placebo network, I shuffle the CB agreement code across firms within 1-digit sector and province cells. If the DiD strategy is valid, then I should not find any effect of the placebo CB shock on wages.

5 Empirical Results

This section presents the main empirical results of the paper. First, I explore the effects of the CB shock and the firm shock on wages and employment. Second, I explore the role of wage floors in the propagation of shocks. Third, I discuss the magnitude of effects using complementary estimates of the effect of the firm shock on revenue, and compare my estimates with the literature. Finally, I present a set of falsification tests and robustness checks.

5.1 Effects on wages and employment

Figure 3 shows the evolution of average wages and employment by level of CB shock and firm shock, relative to 2009. We observe that CB units with larger shocks consistently experience larger increases in wages, but not in employment. On the other hand, there seems to be a small increase in wages, if any, following a firm shock, and it appears that firms in the top tertile of the firm shock experience an increase in employment. The figure also provides suggestive evidence of parallel trends. Next, I ask whether these patterns reflect a causal effect in the context of the DiD model.

Panel (a) of Figure 4 shows estimates of the dynamic DiD model on log mean wages. We observe a strong and stable increase in wages following a CB shock, and a smaller and non-significant increase as response to a firm shock. We cannot reject that pre-trends are zero in anticipation of either shock. Panel (b) of Figure 4 shows estimates of the same model but for employment. We observe a noisy response to the CB shock, which seems to be negative but is not statistically significant. On the other hand, the firm shock seems to increase employment.

Table 1 shows estimates of a static model, where I interact the shock variables with an indicator for $t \geq 2012$ instead of year dummies. Column (1) shows that wages increase by 4.82 percent in response to a 1 percent CB shock, and by 1.73 percent in response to a 1 percent firm shock. While the coefficient on the CB shock is strongly significant ($t = 2.64$), the coefficient on the firm shock is marginally so ($t = 1.86$). Column (4) shows the response of employment, which is statistically indistinguishable from zero for the CB shock ($t = -0.56$), and positive and significant for the firm shock ($t = 2.00$). Columns (5) and (6) show that neither shock seems to affect the share of workers in the main hiring modality, or the probability of firm exit.

Appendix Figure 10 replicates the dynamic model but excluding firms covered by the retail CBA 0130/75, arguably the most binding in the economy. Interestingly, in this case we observe a stronger effect of a firm shock on mean wages, and no effect on employment. The exact value in a static model is 2.85 percent, and is strongly significant ($t = 2.62$). The effect of the CB shock on wages is similar, and the effect on employment is stronger than baseline but still not statistically significant ($t = -0.98$).

5.2 The role of wage floors

Figure 5 shows estimates of the dynamic model using the log wage floor as outcome. Due to data constraints, this model uses a smaller sample of firms in the years 2011–2017, with 2011 as reference year. Panel (a) shows a large and significant effect of the CB shock on wage floors, similar in magnitude to the effect on wages. Column (2) of Table 1 shows a coefficient on the CB shock variable of 5.05 percent ($t = 2.57$), which appears slightly larger than its effect on mean wages. This difference, however, is driven by the different sample. Column (3) of Table 1 shows the effect of the CB shock on the wage "cushion" (the log difference between the wage and wage floor), which is not affected.

Since wage floors are set at the CBA level, the firm shock is not supposed to affect them. Reassuringly, Figure 5 and Table 1 show precisely estimated null effects of the firm shock on wage floors among exporting firms. The standard errors are quite small, implying that effects lower than -0.0073 and larger than 0.0020 are rejected at a 5 percent significance level. At 0.0505, the effect of the CB shock on wage floors is an order of magnitude larger. This finding alleviates concerns that measurement error in the wage-floor variable may be driving the CB effects.

Appendix Figure 11 estimates the effect of CB shocks on wages and the wage floor using all firms covered by the CBA, regardless of their exporting status. We find the same pattern in this larger sample, with similarly-sized effects on mean wages, implying that non-exporting firms are also affected by the CB shock. However, as the effect on wages seems to start in 2011, the effect of wage floors computed relative to 2011 appears a bit smaller.

Heterogeneity by pre-period wages. Following the predictions in Section 2.4, I provide further evidence on the role of wage floors exploiting the heterogeneity in the effect of the CB shock by pre-period wages.

Figure 6 displays the coefficients from static DiD models that interact the CB shock with indicators for each quartile. Panel (a) shows that, after a positive CB shock, firms in the lowest quartile decrease employment. We also observe a decline in the share of workers in the main hiring modality, indicating that full-time workers are more likely to separate. There also significant effects for firms in the third quartile, which increase employment following the CB shock. These patterns low-wage firms moving along the supply curve, and a reduction in monopsony power for medium-wage firms. Panel (b) shows that, while wage floors respond similarly across quartiles, the effect of the CB shock on mean wages seems lower for high-wage firms. We find a strong spillover effects of the wage floor, indicating that wage floors are quite binding in the Argentine labor market. The coefficient for the first quartile may be somewhat lower than in the second one due to the employment response, as high-wage workers (potentially with higher wage floors) are separating from these firms.

Appendix Table 6 provides detailed regression results. The hypothesis of equality of employment responses between the first and third quartiles can be confidently rejected. The hypothesis of equality of response of the share in the main hiring modality between the first and any quartile can be confidently rejected as well. These patterns strongly suggest that the CB shock affects the labor market through wage floors.

5.3 The magnitude of effects

To better interpret the magnitude of the effects, I scale them by the effect of the exporting shocks on wages. Figure 7 shows the effect of the firm shock on product-market sales and labor expenditures using the survey data, which is available for 2010–2016 (excluding 2013). Because these observations do not line up well with the timing of the shocks, I use the panel event-study design described in Appendix E. We observe an increase in both variables, with wage expenditures going up by 0.95 percent and product-market sales going up by 1.1 percent 2 years after the shock.

Following these results, assume that a 10 percent change in z_j translates into a 1.1 percent increase in firm revenue. Then, a 10 percent CB shock can be interpreted as a 1.1 percent increase in firm revenue for all firms in the CBA. Using the results in Table 1, this implies a 10 percent increase in revenue of all firms in the CBA increases wages by $10 \times (0.048/0.11) \approx 4.3$ percent. If the effect of the CB shock on CB revenue is actually larger, then our 4.3 percent estimate can be though of an upper bound. Similarly, a 1 percent increase in firm revenue increases wages by $10 \times (0.017/0.11) \approx 1.5$ percent and employment by $10 \times (0.024/0.11) \approx 3.5$ percent. Using the estimates for the firm shocks that exclude the retail CBA, we would conclude that a 1 percent increase in firm revenue increases wages by $100 \times (0.025/0.11) \approx 2.3$ percent.

Comparison with the literature. The most methodologically related work is Garin and Silvério (2023). Using a similar shift-share strategy in Portugal, the authors find that an "idiosyncratic" exporting shock to a firm increases log sales by 0.143 (Panel A of Table 4) and log hourly wages by 0.022 (Panel A of Table 6), estimates that are comparable in magnitude to mine. The authors do not estimate effects of CB shocks, as a result it is not possible to compare the magnitude of these effects.

Card and Cardoso (2022) study whether changes in mean real valued added per worker in the CB unit predict changes in wage floors, finding that a 10 percent increase in value added per worker increases wage floors by 0.68 percent (Table 6). Unfortunately, I do not observe value added so my estimates cannot be directly compared to theirs. Additionally, my results rely on exogenous variation arising from trade shocks. If the increase is perceived as additional rents for firms then it may lead to stronger demands from workers, and thus lead to larger wage increases.

Jäger et al. (2020) review the rent-sharing literature and find that estimates of rent-sharing elasticities using worker-level micro-data are on average of 0.099, which is again comparable with my firm-level estimates. The authors also finds that industry-level specifications, and especially macro calibrations, find much larger estimates. My estimates suggest an elasticity of the wage floor to average CB revenue of 0.43, which is consistent with the aggregate estimates. This suggests that the level at which wages are set is important to determine the magnitude of rent-sharing.

Effect of firm shock on exports. The firm shock should also affect exports at the firm level. Append Figure 12 shows estimates of the effect of firm shocks on value exported. The DiD strategy, shown in Panel (a), yields noisy results. A key problem is that these estimates compare the difference between each year and 2011 across firms that are exposed to different doses of the firm shock, but 2011 may have already been affected by the shock. In Panel (b) we rely on the event-study design, which uses all variation in product-demand shocks by relying on time-varying versions of z_j. We now observe a strong and stable effect of the firm shock on value exported, of about 30 percent when we compare the average pre-period coefficients with the average post-period coefficients.

5.4 Falsification tests and robustness checks

In general, I find no pre-trends in anticipation of either shock. The CB shock does not predict wages or employment in the pre-period, neither in the sample of exporters nor in the full sample that includes non-exporters. The firm shocks does not predict wages, employment, revenue, or value exported in the pre-period either. The conclusions regarding pre-period coefficients are similar when excluding the retail CBA, which reduces the number of firms in the exporting sample by 28.2 percent. These considerations support the validity of the identifying assumptions, suggesting that firm and CB shocks are plausibly exogenous in the baseline sample.

In this section I present further tests to assess the validity of the results.

Firms with multiple collective bargaining agreements. A minority of firms declare workers under more than one CBA, thus making an interesting case study to assess whether what matters is the CBA that covers the worker instead of other unobserved channels through which shocks may propagate. The rationale is that, if the shocks to firms in the same CBA propagate through other channels, we should not observe CBA-specific effects within the firm. However, if the shock propagates through the CBA that covers the worker, we should observe an effect on wages of workers declared under that CBA.

Figure 8 shows estimates of the dynamic model using all workers in exporting firms that worked in the firm between 2008 and 2014. Panel (a) replicates our main results in this sample: a positive shock to the primary CBA of the worker significantly increases on wages. This specification controls for worker by firm ("match") effects and uses 6-digit economic sector to define local labor markets. Panel (b) estimates a model that uses the CB shock of the worker, instead of the primary CBA in the firm, as treatment variable. Importantly, as it controls for firm by year fixed effects, this demanding specification allows for arbitrary time-varying unobservables at the firm level that should capture any spillover effects of the CB shock through other channels. The figure shows a consistent positive effect of the CB shock on wages.

Appendix Table 8 provides more results from the worker-level analysis using static models. Column (4) shows that the effect of the primary CB shock on wages is driven by workers that are actually declared under the primary CBA. The effect on wages of workers declared under a different CBA is smaller in magnitude and not statistically significant. Columns (1) through (3) show that a shock to the primary CBA in the firm increases wages of this sample of workers when varying local labor market controls, with column (3) corresponding to the specification in Panel (a) of Figure 8. Column (5) replicates the model in Panel (b) of Figure 8.

Controls for local-labor-market effects. Appendix Table 7 shows the results using three alternative specifications to control for local labor market trends: the baseline specification that interacts 4-digit economic sector with province and year fixed effects; the same specification but using 6-digit economic sector instead; and a third specification that uses 2-digit sector and additionally controls for an exporting shock computed similarly to the CB shock but at the 6-digit sector level. Comparing columns (2) to (1) for mean wages, (5) to (4) for employment, and (8) to (7) for mean wage floors, we find that using 6-digit instead of 4-digit sector to define local labor markets does not substantively alter the results. Columns (3), (6), and (9) control for the 6-digit sector shock directly. Conclusions are, once again, very similar. The only difference is that the point estimate of the employment effect is positive, although still not statistically significant. The 6-digit shock does not appear to affect wages, but it does seem to lower employment. Reassuringly, column (9) shows precisely estimated null effects of the 6-digit shock on wage floors.

Placebo collective bargaining network. To assess the validity of the main empirical strategy, I estimate the DiD model using a placebo-network CB shock. To do so I construct a placebo network by randomly shuffling the CBA code across firms within each 1-digit sector and province.

Appendix Figure 13 shows estimates of the dynamic model using the placebo-network CB shock. The figure shows precisely estimated zero effects on wages and wage floors.

Other robustness checks. Appendix Table 9 replicates the main estimates for wages and employment, but changing the set of controls included in the regression. I find very similar results when excluding the firm-level controls (baseline firm size and share of workers in the main hiring modality), controlling for the pre-period firm shock directly, and excluding the control for the pre-period CB shock. Appendix Figure 14 replicates Figure 4 keeping firms with extreme values of the pre-period shock. The effects of CB shock and those of the firm shock on employment are very similar to the baseline estimates. However, for the effect of the firm shock on wages there is a significant pre-period coefficient in 2007, and no effect of the firm shock after 2011. While I find the exclusion of these firms to be justified, it is important to note that the results of the firm shock on wages are not robust to their inclusion. Appendix Figure 15 replicates Figure 4 using the panel event-study design in a comparable sample that includes the retail CBA, and suggests very similar conclusions as the baseline estimates.

Appendix Table 10 replicates the main estimates as well, but varying the set of CB units included in the sample. Column (2) shows that keeping CB units with less than 30 firms in the sample lowers the estimated effect of the CB shock on wages, although the coefficient is still significant at the 10% level ($t = 1.90$). Column (3) shows that dropping CB units with more than 100 firms in the sample seems to increase this effect. It appears that large CB units experience a stronger effect of the CB shock on wages. Column (4) shows results of the static model when excluding the retail CBA, i.e., the analogous specification to Appendix Figure 10 discussed before. Columns (5) through (8) replicate the finding of non-significant effects of the CB shock on employment.

6 Structural Model

While the empirical estimates indicate that shocks propagate through the CB network, they cannot inform us about how shocks would propagate under alternative CB networks. In this section, I present a structural model with homogeneous workers, heterogeneous local labor markets. The model is later estimated and used to analyze the role of the CB network on the propagation of shocks.

6.1 Set-up

There is a fixed population of N_r in each region $r \in \mathcal{R}$.[16] Each region is divided in local labor markets $g \in \mathcal{G}$, each with an economic sector $k \in \mathcal{K}$. I denote by $\mathcal{K}1$ the set of first-digit grouping of sectors. Note that a given sector and region cell may be partitioned into multiple local markets. Local labor markets contain a continuum of firms, indexed by j. The measure of firms in each

[16] Think of these as distant regions with disjoint labor markets.

local labor market is given by M_g. The collective bargaining network is a partition of local labor markets denoted by $\mathcal{C}$. Within each CB unit $c \in \mathcal{C}$ a union and an employer association bargain over a single wage floor $\underline{w}_c$ binding for all local labor markets in the unit.

Different actors take decisions sequentially. First, CB units play a simultaneous-move game to determine the set of wage floors $\{\underline{w}_c\}_{c \in \mathcal{C}}$. Second, firms j in each $g \in \mathcal{G}$ draw productivities $\varphi(j)$ from a known distribution $F_g(\varphi)$. Third, workers in each region r decide, first, whether to enter the formal labor market or not, and second, labor supply to each firm in the formal labor market. Fourth, firms in each local labor market g decide employment and wages in imperfectly competitive labor markets, and wage indexes adjust to clear the labor market. Finally, production takes place and workers earn the wage $w(j)$ in their firm j.

To focus on the role of the CB network, I abstract away from the goods market. I will model economic shocks as a change in local productivity.

6.2 Solving the model

Unions and employers anticipate the response of the labor market when negotiating. Thus, I solve the model backwards starting with the worker and firm's problems and then moving into the bargaining game.

6.2.1 Labor supply

Conditional on formal labor market entry, a worker i in region r has an indirect utility of working for firm j given by $V_{ri}(j) = A_{k1(j)} w(j) \xi_i(j)$. $A_{k1(j)}$ is an amenity value specific to the 1-digit sector of firm j. I assume that the idiosyncratic component $\xi_i(j)$ follows a Frechét (or type-2 extreme value) distribution with scale parameter η, as is standard in the literature of discrete choice models.[17] Then, it can be shown that labor supply to a firm located in region r is

$$\ell(j) = \left[\frac{A_{k1(j)} w(j)}{W_r}\right]^\eta \tag{6}$$

where W_r is an aggregate wage index specific to region r. Derivations are available in Appendix F.1. Note that η can be interpreted as the elasticity of labor supply to the firm.

Since $\xi_i(j)$ follows a Frechét distribution, the expected utility of formal employment in region r is proportional to the wage index in r,

$$V_r = \Gamma\left(\frac{\eta - 1}{\eta}\right) W_r, \tag{7}$$

where $\Gamma(\cdot)$ is the gamma function.

Before choosing a firm, workers decide whether to work formally or not. Workers' preferences

[17] Following results in McFadden (1978), similar expressions can be derived using other members of the Generalized Extreme Value family.

for formal employment in r depend on the value of formal employment V_r, the value of non-formal employment b_r, and an idiosyncratic shock that follows a Gumbel (or type-1 extreme value) distribution with shape parameter ζ. The resulting formal employment share is given by

$$\mu_r = \frac{V_r^\zeta}{V_r^\zeta + b_r}. \tag{8}$$

A larger value of ζ implies a larger elasticity of the employment share to changes in V_r.

6.2.2 Labor demand

Each firm j draws a productivity $\varphi(j) \geq 0$ from a distribution $F_g(\varphi)$ defined over $[\varphi_{g0}, \infty)$. Firms in local labor market g maximize profits with a linear technology:

$$(\ell(j)^*, w(j)^*) = \arg\max_{\ell,w} \left\{ \varphi(j)\ell - w\ell \;\middle|\; \ell = \left(\frac{A_{k1(j)}w}{W_{r(j)}}\right)^\eta,\ w \geq \underline{w}_c \right\}. \tag{9}$$

The wage floor may be binding or not. If not, we say that the firm is *unconstrained*, in which case the solution to the firm's problem for a firm with productivity φ is $w(\varphi) = \mu\varphi$, where $\mu = (\eta/(\eta+1))$ is the markdown factor. If the wage floor is binding and the firm is *constrained* we have that $w(\varphi) = \underline{w}_c$. The quantity of labor can be obtained by replacing the wage in the labor supply curve (6). Appendix F.1 shows exact expressions for employment and profits.

If the wage floor is high enough, the threshold that determines whether firms are constrained in g is given implicitly by $w(\overline{\varphi}) = \underline{w}_c$, which results in

$$\overline{\varphi}_g = \mu^{-1}\underline{w}_c. \tag{10}$$

Firms with $\varphi \leq \overline{\varphi}$ will pay exactly the wage floor. Similarly, firms leave the market if ex-post they experience negative profits $\pi(\underline{\varphi}) < 0$, implying thresholds

$$\underline{\varphi}_g = \underline{w}_c. \tag{11}$$

Note that thresholds do not vary for g's in the same CBA. If $\underline{w}_c < \mu\varphi_{g0}$ no firm will be constrained.

The distance between the thresholds depends on η. A higher η implies lower heterogeneity in idiosyncratic worker-level preferences $\xi_i(j)$, and so more responsiveness to wages. In the extreme case of $\eta \to \infty$, the markdown vanishes and the wage floor is only binding for the lowest productivity firm. A lower η implies more heterogeneity in $\xi_i(j)$, and so lower responsiveness to wages. If $\eta \to 0$, the markdown goes to 0 and so the bargained wage floor becomes binding for all firms.

Parametrization and the share of firms bunching. I assume that productivities in local labor market g are drawn from a Pareto distribution with shape $\alpha > 1$ which cdf is given by

$$F_g(\varphi) = 1 - \left(\frac{\varphi_{g0}}{\varphi}\right)^{\alpha} \tag{12}$$

for $\varphi \geq \varphi_{g0}$ and zero otherwise. I denote by $F_g(\varphi|x)$ the conditional cdf of productivity given a minimum value of $x > \varphi_{g0}$. The fraction of "possible" productivities that will be observed is given by $1 - F_g(\varphi^{\min})$, where $\varphi^{\min} = \max\{\varphi_{g0}, \underline{\varphi}_g\}$. The total measure of firms in the market is then $M_g\left(1 - F_g(\varphi^{\min})\right)$. Note that this quantity is non-increasing in the wage floor (if $\underline{w}_c > \varphi_{g0}$, then the measure of firms is decreasing in the floor).[18]

The share of observed firms paying the wage floor, or "bunching," can be computed using the conditional cdf $F_g(\varphi|\varphi^{\min})$. If $\underline{w}_c < \mu\varphi_{g0}$ the share is zero. If $\underline{w}_c > \varphi_{g0}$ then $\varphi^{\min} = \underline{w}_c$ and the share of firms bunching takes its maximum value of $1 - \left(\frac{\eta}{\eta+1}\right)^{\alpha}$. Otherwise, that share varies between 0 and this maximum value. Appendix Figure 16 illustrates the productivity distribution with a binding wage floor, for a situation where the share of firms bunching is in the intermediate case. Panel (a) shows the pdf. Panel (b) illustrates the wage paid at each productivity level.

Computing aggregate quantities. To compute average wages across active firms, or the share of firms bunching, I integrate over the distribution of observed firms in g. The minimum value of this integration might be φ_{g0}, $\underline{\varphi}_g$, or $\overline{\varphi}_g$ depending on the value of the wage floor $\underline{w}_{c(g)}$. To compute aggregate labor demand I integrate over the distribution of "possible" firms in g, so the minimum value will always be φ_{g0}. This is the relevant quantity to determine the equilibrium in bargaining, as the measure of firms in the market would then be allowed to respond to the wage floor. Appendix F.1 shows expressions for aggregate quantities at the local labor market level.

6.2.3 Nash bargaining

Each CB unit negotiates over wage floors $\{\underline{w}_c\}_{c\in\mathcal{C}}$. I assume that both unions and employer associations are risk neutral, and that both parties have rational expectations in the sense that they know the distributions $\{F_g(z)\}_{g\in\mathcal{G}}$ and correctly anticipate the outcomes following their choice of $\underline{w}_c$. As a result, I do not use expectations in the below.

Following the framework in Section 2, I assume that preferences are given by $U_c\left(\underline{w}_c, \underline{\mathbf{w}}_{-c}\right) = \sum_g WB_g$ and $\Pi_c\left(\underline{w}_c, \underline{\mathbf{w}}_{-c}\right) = \sum_g\left(R_g - WB_g\right)$, respectively. Preferences depend on the wage floor $\underline{w}_c$ by altering the share of firms bunching and the cost of labor. They also depend on the wage floor of other CB units $\underline{\mathbf{w}}_{-c}$, which affects the equilibrium wage index in each region.

This formulation assumes away the outside option of workers. This is so because, given parameter values in the following section, I find that the weight ω_c is quite large. A possible

[18] Note that the measure of firms responds to the wage floor via changes in the share. An alternative specification would be to allow M_g to vary with $\underline{w}_c$ and always normalize the share to 1. This could be done by assuming some entry cost in each local labor market, and imposing a free-entry condition on profits that would pin down M_g.

justification for these functional forms is that unions and employer associations receive a fee proportional to each payslip and profits, respectively, and they aim to maximize their revenue.[19] In any case, adding the outside option of workers would not substantively alter the results.

Solving the Nash bargaining problem. Letting β_c denote the bargaining power of the union, the Nash bargaining problem can then be written as in (1). Denoting $WB_c = \sum_g WB_g$ and $R_c = \sum_g R_g$, the solution to a single problem is given by the Nash split rule $WB_c\left(\underline{w}_c, \underline{\mathbf{w}}_{-c}\right) = \omega_c R_c\left(\underline{w}_c, \underline{\mathbf{w}}_{-c}\right)$, where $\omega_c \in (0,1)$ is a weight that depends on the wage floors, given in (3). Importantly, the weight ω_c is affected by the derivatives of U_c and Π_c with respect to $\underline{w}_c$, which incorporate the effect of the wage floor on the aggregate wage index.

Nash-in-Nash solution. Horn and Wolinsky (1988) introduced the idea in the analysis of bilateral monopolies. Davidson (1988) uses a similar concept analyzing a two-union bargaining game. In a Nash-in-nash solution, each individual problem results in a Nash equilibrium given that the wage floors of other CBAs are in equilibrium as well. The solution assumes that players in a given CB unit do not take into account the effect of their decision on the choice of other CB units.[20] In the setting of this model, $\{\underline{w}_c^*\}_{c\in\mathcal{C}}$ is a Nash-in-Nash solution if

$$\underline{w}_c^* = \arg\max_{\underline{w}} U_c\left(\underline{w}, \underline{\mathbf{w}}_{-c}^*\right)^{\beta_c} \Pi_c\left(\underline{w}, \underline{\mathbf{w}}_{-c}^*\right)^{1-\beta_c}, \tag{13}$$

and this holds for all $c \in \mathcal{C}$.

6.3 Equilibrium

Given a collective bargaining network $\mathcal{C}$ and a set of parameters, an equilibrium is defined as a set of wage floors $\{\underline{w}_c^*\}_{c\in\mathcal{C}}$, regional wage indexes $\{W_r^*\}_{r\in\mathcal{R}}$, and employment shares $\{\mu_r^*\}_{r\in\mathcal{R}}$ such that: (1) the Nash-in-Nash bargaining game is solved, (2) labor markets clear in each region. Appendix F.2 formally defines the equilibrium.

In general, there is no closed form solution for the vector of equilibrium wages. Appendix F.2 shows the algorithm I use to compute the equilibrium for a given set of parameters. It also shows the derivative of the wage index in a region with respect to a wage floor, which is required to solve the Nash bargaining problem. As one might expect, the sign of this derivative depends on the sign of the effect of the wage floor on employment.

[19] Gürtzgen (2009a) theoretically explores the effect of different bargaining structures in an oligopoly model and similarly assumes that unions maximize the wage bill.

[20] This is a debatable assumption in the context of a single union signing multiple CBAs, as it implies that unions do not internalize the effect of their decision across CBAs. While we abstract from this issue by assuming a unique union per c, we note that Collard-Wexler et al. (2019) show that the Nash-in-nash solution can be micro-founded in a fully noncooperative environment where market participants internalize the interdependence of their potentially multiple bargains.

7 Estimation and Validation of Structural Model

In this section I discuss the construction of a dataset at the local labor market level and the estimation of the model parameters. I also show that the model is able to replicate the estimated effects of CB shocks on wages. I postpone the counterfactual exercises to the next section.

7.1 Local labor markets data

I specify sectors $k \in \mathcal{K}$ as a coarsening of the 4-digit sectors in the data, and regions $r \in \mathcal{R}$ as a grouping of provinces in Centro (center, including Buenos Aires), Cuyo (west), Norte (north), and Patagonia (south). I drop the 1-digit sectors associated with agricultural production, education and government.[21] I further divide the sector by region cells using the observed CB network $\mathcal{C}$. If a CBA has enough workers and/or firms, I keep it as a separate local labor market. If not, I assign it to a "local CBA" category. Appendix F.3 provides details.

I estimate wage floors by taking the mean of the firm-level average wage floor across workers in each CBA, weighting by the share of workers with an assigned wage floor. I allow regional wage floors within a CBA only if the region's average wage floor is sufficiently different from the rest. Appendix Figure 17 shows the distribution of estimated wage floors, in which we note a much wider variation in wage floors of local CBAs. To estimate the share of firms constrained by the wage floor I use the workers that were assigned a wage floor and compute the average firm-level deviation it. To account for part-time work and measurement error, I define a worker as a "buncher" (i.e., with a deviation of zero) if the deviation is within a range of the wage floor or half the wage floor. Then, the share of firms constrained is simply the share of firms where all workers are bunchers. I obtain the average wage and employment using the firm-level data as well, adjusting for (estimated) part-time work.

Table 14 provides summary statistics of the local labor markets data. There are 775 CB units, of which 504 are local. 57.2% of local labor markets are in the region "Centro," 23.2% are covered by a local CB unit, and 18.6% are covered by the retail CBA. We observe a few small local labor markets where the mean wage is lower than the wage floor, which reflects that such markets excessively use part-time employment. I account for this when computing the share of firms bunching. The measure of firms in each local labor market M_g is normalized so that $\frac{1}{|\mathcal{G}|}\sum_g M_g = 1$. The table also shows characteristics of the local labor markets in the data in 2011–2012 and 2014–2015. We rely on the 2011–2012 estimates, as they correspond to the earliest period before the full impact of the trade shocks.

7.2 Calibration and Estimation

I use several strategies to estimate the model parameters, which are summarized in Appendix Table 11 and detailed in this section. Appendix F.4 provides details.

[21] This is because bargaining in these sectors is regulated by different regimes. Additionally, the agricultural sector represents a small share of employment.

Worker problem. To estimate the preference heterogeneity parameter η and the amenity values $\{A_{k1}\}_{k1\in\mathcal{K}1}$, I leverage the log-linear relationship between firm size and firm wages implied by the labor supply to the firm (6). I find a value of $\eta \approx 4.10$, which is in line with the literature. This value implies a markdown factor of unconstrained firms of $\mu \approx 0.80$. I calibrate the parameter indicating heterogeneous preferences for formal employment using evidence on the extensive-margin labor supply elasticity from the literature and data on the share of formal employment in the labor market. I set $\zeta \approx 0.28$.

Productivity distributions. I calibrate the common shape parameter α so that the model admits the 99.5th percentile of the share of firms bunching at the wage floor in 2014–2015, obtaining $\alpha \approx 5.62$. To estimate the minimum value of the productivity distributions $\{\varphi_{g0}\}_{g\in\mathcal{G}}$, I invert the closed form expression for the share of firms bunching at the wage floor implied by the model. I use the wage floor in each local labor market, and the values of η and α from above. Appendix Table 14 shows summary statistics of the estimated minimum productivity values. Importantly, I estimate the minimum productivities at two moments in time, which allows me to construct productivity shocks at the local labor market level.

Outside options. Using estimates from above, the share of formal firms in each region from household survey data, and the market-clearing condition in each region, I compute $\{W_r\}_{r\in\mathcal{R}}$ and $\{V_r\}_{r\in\mathcal{R}}$. Then, I invert equation (8) to obtain the outside option parameters $\{b_r\}_{r\in\mathcal{R}}$.

Bargaining power. I invert equation (2) to obtain β_c for each c. This condition will hold in any equilibrium where the objective function of the bargaining problem is strictly concave.

The key variation used to pin down these parameters comes from the ratio of the derivatives of U and Π with respect to the wage floor, evaluated at the equilibrium. If the ratio is low, the union is relatively closer to its optimal wage floor (where $dU/d\underline{w}_c = 0$), suggesting stronger bargaining power. The distribution of the ratio of derivatives is shown in Panel (a) of Appendix Figure 20. We observe a large variation in the ratio. While this suggests a relatively weak position of unions, it is hard to make strong statements as these estimates are dependent on the functional forms assumed in the model.

I check whether the bargaining power parameters correspond to a global maximum, and find that this is not the case for the retail CBA. This CBA is large, and as a result it has significant general equilibrium effects and covers heterogeneous local labor markets. As a result, the objective function is not strictly concave, and the bargaining power actually corresponds to a local maximum. I maintain the wage floor of this CBA fixed when computing counterfactual equilibria.

Panel (b) of Appendix Figure 20 shows the estimated bargaining power parameters. We observe a great deal of heterogeneity, though most values are under 0.25. Appendix Figure 21 shows the correlation between the estimated bargaining power parameters and CBA-level observables. Panel (a) suggests a weakly positive correlation with employment under the CBA.

Panel (b) shows a positive correlation with the average outside option in the CBA, especially for local CB units. Panel (c) shows a weak negative correlation with the minimum productivity under the CBA. Overall, a great deal of variation in bargaining power across CBAs cannot be accounted for by observable characteristics.

7.3 Validation

I validate the model comparing data moments with model-based predictions.

First, I use the estimated minimum productivities to compute the average wage in each local labor market, as implied by the model. Appendix Figure 18 shows that the model does a great job at predicting the average wage in each local labor market, even though these data were not used in estimation. Interestingly, the share of firms bunching (which is a key input to estimate the minimum productivities) is not correlated with the average wage, as shown in Panel (a) and Appendix Figure 19.

Second, Appendix Figure 19 shows that the model does a good job at replicating the patterns in the data. The top row shows that average wages are nearly a constant above the wage floors, both in the data and the model. Unsurprisingly, as production technology is very simple in the model, the model shows less variation in average wages than the data. The bottom row shows that the wage floor is nearly uncorrelated with the share of firms bunching, though local labor markets with a very small share of firms bunching tend to have higher average wages. This pattern holds in the data and the model as well.

7.4 Replicating the effects of CB shocks

I estimate the effect of trade shocks at the local labor market level both in the data and the model. To do that I first estimate the effect of trade shocks on the aggregate revenue using the survey of businesses (ENDEI). Appendix Table 15 shows that aggregate revenue increases by about 22% in exporting local labor markets, and this conclusion is similar to excluding the largest CB units in the data. There is also a non-significant effect on non-exporting local labor markets of about 6%. Then, I take the estimated model in 2011–2012 and simulate shocks to minimum productivity that would result in the same changes in aggregate revenue as suggested by the survey data. I re-compute the model equilibrium using the new minimum productivities, and estimate the effect of the shocks on wages using a shift-share strategy.

Appendix Table 16 estimates the effects of CB shocks on log wages and log wage floors, in the aggregate data and the model-generated data. The data are more noisy, as one would expect. The model is able to replicate the spillover effects. However, the model seems to underestimate the degree of spillovers. The reason for this is that the model does not account for effects of the wage floor on unconstrained firms.

8 Model-Based Counterfactuals

In this section I explore the role of collective bargaining in wage-setting by estimating the effect of shocks under counterfactual bargaining networks.

8.1 Counterfactual networks

My goal is to construct counterfactual bargaining networks that are plausible, in the sense that they follow the same rules as those in other countries. I construct counterfactual bargaining networks as follows. First, I simplify the baseline network by removing some local labor markets and assigning to them the most common CB unit in their economic sector and region.. Then, I divide this simplified network in regions. I call these networks “baseline simple” and “baseline region,” respectively. Lastly, I split the baseline simple network according to economic sectors. In order to maintain the average level of bargaining power constant, I assign bargaining power parameters to the new CB units by averaging the bargaining power parameters of observed CB units, weighting by the measure of local labor market size M_g.

In terms of the classification in Bhuller et al. (2022), these networks vary the degree of “vertical coordination” of bargaining. Examples of countries with mostly sectoral bargaining are Italy, Portugal, or France. Examples of countries with mostly local bargaining are the US, the UK, or Japan. I classify the counterfactual networks based on the average number of local labor markets per CB unit. The baseline network contains a mix of both types of bargaining, and the average number is about 4. The simplified baseline networks are more centralized, with an average of about 5 and 8 local labor markets per CB unit, respectively. The sectoral networks are more decentralized, with an average of about 2 to 3 local labor markets per CB unit. Finally, the local network is the most decentralized, and imposes that each local labor market is a separate CB unit.

8.2 Shock Propagation and Bargaining Centralization

In this section I explore how the degree of centralization of bargaining affects the propagation of shocks. Figure 9 shows the correlation of shocks and wages across local labor markets for the different bargaining networks. By construction, this correlation is one for the local network. We observe a non-monotonic relationship between the correlation and the degree of centralization of bargaining. The data suggests a u-shaped relationship. Local and highly centralized bargaining result in a high correlation between shocks and wages, or in other words, a high degree of propagation of shocks. On the other hand, sectoral bargaining results in a lower degree of propagation of shocks.

What explains these patterns? A network will increase the degree of shock propagation if the negotiated wage floor has a large impact on the local labor market. Figure 10 shows the variability in wages across these networks. Panel (a) shows that wage floors are more volatile under more centralized bargaining networks. However, as shown in Panel (b), this does not translate into more volatile mean wages. For this to be the case, the network must result in high levels of firms bunching at the wage floor. Appendix Figure 22 shows that the "baseline region" network, for which the degree of shock propagation is highest, also results in a high degree of firms bunching at the wage floor compared to the other baseline networks. The local network and the sectoral networks result in a high degree of firms bunching as well, but they do not connect many local labor markets which results in a low degree of shock propagation.

8.3 Discussion

Calmfors and Driffill (1988) suggest that extreme degrees of centralization of bargaining perform best in terms of macroeconomic performance. Their key insight is that medium degrees of decentralization will generate negative externalities in other sectors that are ignored by unions, whereas local bargaining or national bargaining will internalize these negative effects either by competitive forces or by a monopolistic union. Boeri et al. (2021) suggests that high centralization in Italy relative to Germany results in higher unemployment in lower-productivity regions in Italy. These authors emphasize the importance of increased wage rigidity that results from the centralization of bargaining.

I focus on a related question, whether the degree of centralization of bargaining affects the variability of wages in response to shocks. We know that concentrated shocks can have large effects, as a result bargaining systems with more shock propagation may be more resilient as the effects of shocks are more evenly distributed across the economy, effectively "sharing the risk" of shocks. My findings suggest that regional centralization may be a way to increase risk sharing. This arrangement generates endogenous wage floors that are more aligned with local labor market conditions, and as a result more binding, but also prevents concentrated local shocks from being fully transmitted to local wages, thereby dissipating their effects.

9 Conclusions

This paper studied the role of collective bargaining (CB) in mediating the effects of shocks across firms and regions. First, relying on a novel dataset to identify the CB unit that covers each firm, I showed that shocks to product demand arising from exposure to International markets propagate to other firms that share the same CB unit. The results indicate that collective negotiations are the main channel for workers to gain from firms' rents, and they also indicate that the risk of shocks is shared among firms in the same CB unit. The evidence suggests that the wage floor is the main channel through which CB shocks affect wages.

Second, I developed and estimated a structural model of the labor market with CB to assess how shocks would propagate under different CB networks. The model showed that more centralized bargaining does not necessarily result in more shock propagation. The estimates suggest that networks with sectoral bargaining that result in more binding wage floors do result in more shock propagation. An example for Argentina is a CB network that splits bargaining units by region.

This article leaves several questions unanswered. First, the article focuses on how firm wages are affected and does not speak to the value for workers of decreasing the risk of shocks. This might be important to quantify the welfare contribution of the insurance provided by sectoral CB. Second, the analysis ignores potential effects of collective bargaining on informality, which may especially important in developing countries. While in my setting of exporting firms there is little scope for informality, this may not be the case for other types of shocks. Third, the model abstracts from several features of the labor market that may be important for a more complete analysis of the effects of CB, such as unemployment. These questions present interesting avenues for future research.

References

Abowd, J. A. and Lemieux, T. (1993). The effects of product market competition on collective bargaining agreements: The case of foreign competition in Canada. *Quarterly Journal of Economics*, 108(4):983–1014.

Adão, R., Arkolakis, C., and Esposito, F. (2022). General equilibrium effects in space: Theory and measurement. *Working Paper*.

Ahlfeldt, G. M., Roth, D., and Seidel, T. (2022). Optimal minimum wages. Technical Report DP16913, Centre for Economic Policy Research.

Autor, D., Dorn, D., and Hanson, G. (2013). The China syndrome: Local labor market effects of import competition in the United States. *American Economic Review*, 103(6):2121–68.

Bhuller, M., Moene, K. O., Mogstad, M., and Vestad, O. L. (2022). Facts and fantasies about wage setting and collective bargaining. *Journal of Economic Perspectives*, 36(4):29–52.

Boeri, T., Ichino, A., Moretti, E., and Posch, J. (2021). Wage equalization and regional misallocation: evidence from italian and german provinces. *Journal of the European Economic Association*, 19(6):3249–3292.

Borusyak, K., Dix-Carneiro, R., and Kovak, B. (2022a). Understanding migration responses to local shocks. *Available at SSRN 4086847*.

Borusyak, K., Hull, P., and Jaravel, X. (2022b). Quasi-experimental shift-share research designs. *Review of Economic Studies*, 89(1):181–213.

Calmfors, L. and Driffill, J. (1988). Bargaining structure, corporatism and macroeconomic performance. *Economic policy*, 3(6):13–61.

Card, D. (1990). Unexpected inflation, real wages, and employment determination in union contracts. *The American Economic Review*, 80(4):669–688.

Card, D. (1996). The effect of unions on the structure of wages: A longitudinal analysis. *Econometrica*, pages 957–979.

Card, D. and Cardoso, A. R. (2022). Wage flexibility under sectoral bargaining. *Journal of the European Economic Association*, 20(5):2013–2061.

Card, D., Cardoso, A. R., Heining, J., and Kline, P. (2018). Firms and labor market inequality: Evidence and some theory. *Journal of Labor Economics*, 36(S1):S13–S70.

Cardoso, A. R. and Portugal, P. (2005). Contractual wages and the wage cushion under different bargaining settings. *Journal of Labor Economics*, 23(4):875–902.

Chetty, R., Guren, A., Manoli, D., and Weber, A. (2011). Are micro and macro labor supply elasticities consistent? a review of evidence on the intensive and extensive margins. *American Economic Review*, 101(3):471–475.

Collard-Wexler, A., Gowrisankaran, G., and Lee, R. S. (2019). “Nash-in-Nash” bargaining: A microfoundation for applied work. *Journal of Political Economy*, 127(1):163–195.

Corneo, G. (1995). National wage bargaining in an internationally integrated product market. *European Journal of Political Economy*, 11(3):503–520.

Datta, N. (2023). The measure of monopsony: The labour supply elasticity to the firm and its constituents. Discussion Paper 1930, Centre for Economic Performance, London School of Economics and Political Science.

Davidson, C. (1988). Multiunit bargaining in oligopolistic industries. *Journal of Labor Economics*, 6(3):397–422.

Dix-Carneiro, R. and Kovak, B. K. (2017). Trade liberalization and regional dynamics. *American Economic Review*, 107(10):2908–46.

Felix, M. (2022). Trade, labor market concentration, and wages. *Unpublished Manuscript.*

Freeman, R. B. and Medoff, J. L. (1984). *What do unions do?* Basic Books.

Freyaldenhoven, S., Hansen, C., Pérez, J. P., and Shapiro, J. M. (forthcoming). Visualization, identification, and estimation in the linear panel event-study design. *Advances in Economics and Econometrics - Twelfth World Congress.*

Galichon, A. (2022). 'math+econ+code' masterclass on equilibrium transport and matching models in economics.

Garin, A. and Silvério, F. (2023). How Responsive Are Wages to Firm-Specific Changes in Labour Demand? Evidence from Idiosyncratic Export Demand Shocks. *The Review of Economic Studies*, page rdad069.

Gaulier, G. and Zignago, S. (2010). BACI: International trade database at the product-level. the 1994-2007 version. Working Papers 2010-23, CEPII.

Gürtzgen, N. (2009a). Firm heterogeneity and wages under different bargaining regimes: does a centralised union care for low-productivity firms? *Jahrbücher für Nationalökonomie und Statistik*, 229(2-3):239–253.

Gürtzgen, N. (2009b). Rent-sharing and collective bargaining coverage: Evidence from linked employer–employee data. *Scandinavian Journal of Economics*, 111(2):323–349.

Holden, S. (1988). Local and central wage bargaining. *The Scandinavian Journal of Economics*, 90(1):93–99.

Horn, H. and Wolinsky, A. (1988). Bilateral monopolies and incentives for merger. *The RAND Journal of Economics*, 19(3):408–419.

Hummels, D., Jørgensen, R., Munch, J., and Xiang, C. (2014). The wage effects of offshoring: Evidence from danish matched worker-firm data. *American Economic Review*, 104(6):1597–1629.

Jäger, S., Schoefer, B., Young, S., and Zweimüller, J. (2020). Wages and the Value of Nonemployment*. *Quarterly Journal of Economics*, 135(4):1905–1963.

La Nación (2017). Para ganar competitividad, congelan salarios por dos años en la industria fueguina. Newspaper article published on 11-17-2017. Access here.

La Nación (2022). El sindicato del neumático desafió a Sergio Massa y seguirá con el paro. Newspaper article published on 09-28-2022. Access here.

Liao, S., Kim, I. S., Miyano, S., and Zhu, F. (2020). concordance: Product concordance. R package version 2.0.0.

Manning, A. (2011). Chapter 11 - imperfect competition in the labor market. volume 4 of *Handbook of Labor Economics*, pages 973–1041. Elsevier.

McFadden, D. (1978). Modeling the choice of residential location. *Transportation Research Record*, (673).

Ministerio de Trabajo, Empleo y Seguridad Social (2022a). Simplificación registral. Data produced by the Dirección de Estudios y Estadísticas Laborales. Last accessed: June 2023.

Ministerio de Trabajo, Empleo y Seguridad Social (2022b). Sistema integrado previsional argentino. Data produced by the Dirección de Estudios y Estadísticas Laborales. Last accessed: June 2023.

Ministerio de Trabajo, Empleo y Seguridad Social (2023). Cobertura e incidencia de los convenios colectivos de trabajo. Data produced by the Dirección de Estudios y Estadísticas de Relaciones de Trabajo. Date accessed: June 2023.

Monte, F., Redding, S. J., and Rossi-Hansberg, E. (2018). Commuting, migration, and local employment elasticities. *American Economic Review*, 108(12):3855–3890.

Naylor, R. (1998). International trade and economic integration when labour markets are generally unionised. *European Economic Review*, 42(7):1251–1267.

Oi, W. Y. and Idson, T. L. (1999). Chapter 33 firm size and wages. volume 3 of *Handbook of Labor Economics*, pages 2165–2214. Elsevier.

Palomino, H. and Trajtemberg, D. (2006). Una nueva dinámica de las relaciones laborales y la negociación colectiva en la argentina. *Revista de trabajo*, 2(3).

Parente, R. (2022). Minimum wages, inequality, and the informal sector. *Unpublished manuscript.*

Plasman, R., Rusinek, M., and Rycx, F. (2007). Wages and the bargaining regime under multi-level bargaining: Belgium, Denmark and Spain. *European Journal of Industrial Relations*, 13(2):161–180.

Pontoni, G. and Trajtemberg, D. (2017). Estructura, dinámica y vigencia de los convenios colectivos de trabajo sectoriales del ámbito privado (1975-2014). *Estudios del trabajo*, (54):5–26.

Rose, N. L. (1987). Labor rent sharing and regulation: Evidence from the trucking industry. *Journal of Political Economy*, 95(6):1146–1178.

Rusinek, M. and Rycx, F. (2013). Rent-sharing under different bargaining regimes: Evidence from linked employer–employee data. *British Journal of Industrial Relations*, 51(1):28–58.

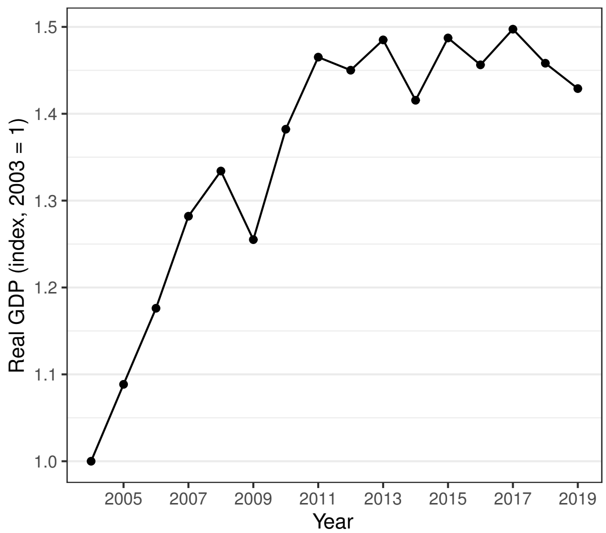
Topalova, P. (2010). Factor immobility and regional impacts of trade liberalization: Evidence on poverty from india. *American Economic Journal: Applied Economics*, 2(4):1–41.

Van Reenen, J. (1996). The creation and capture of economic rents: Wages and innovation in UK manufacturing plants. *Quarterly Journal of Economics*, 111:195–226.

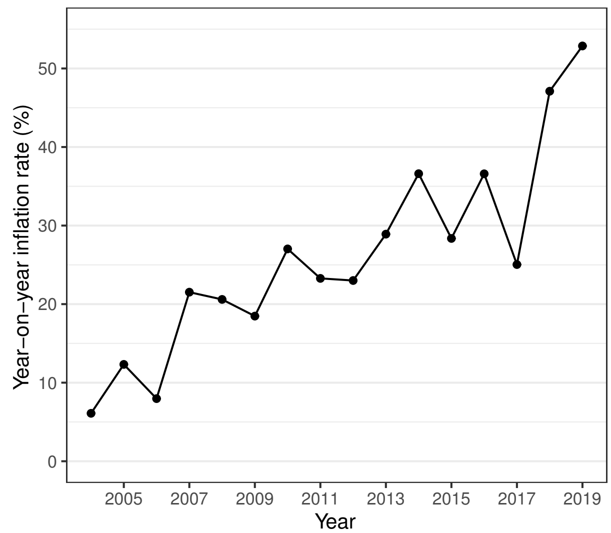
Visser, J. (2019). ICTWSS database. version 6.1.

Figure 1: Performance of Argentinian economy, 2004–2019

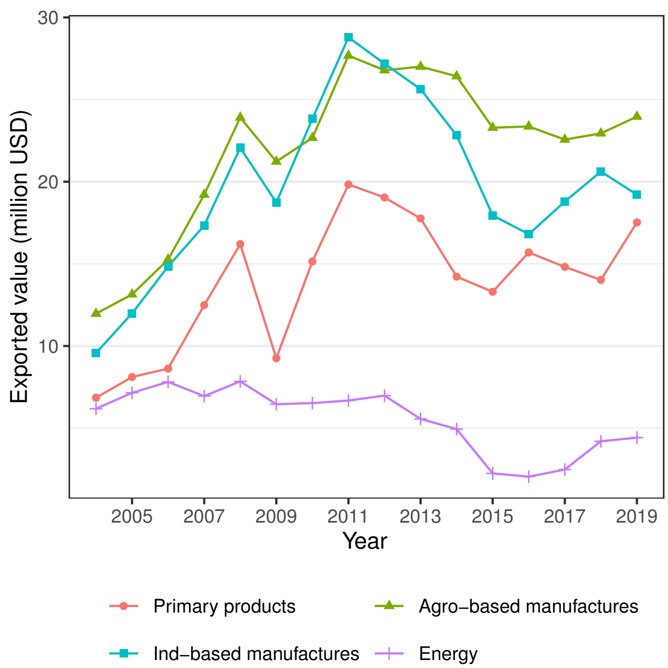
(a) Real Gross Domestic Product



(b) Yearly inflation rate



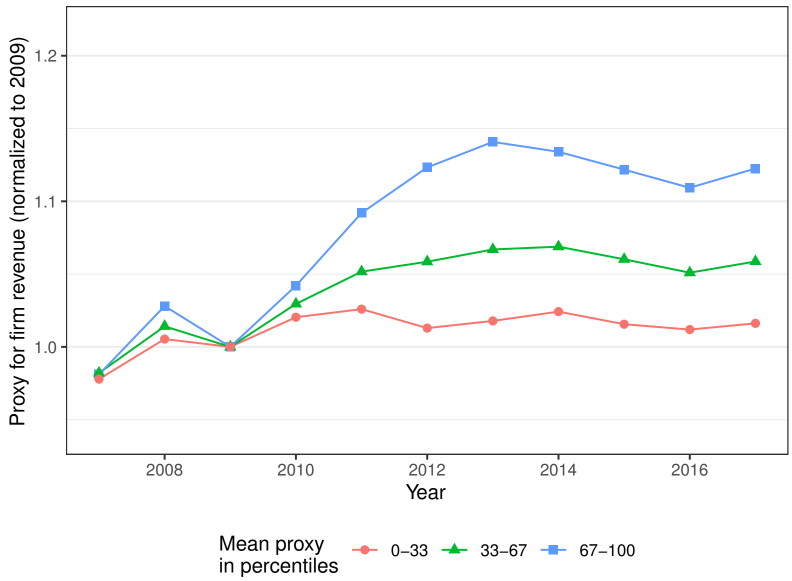
(c) Total exported value



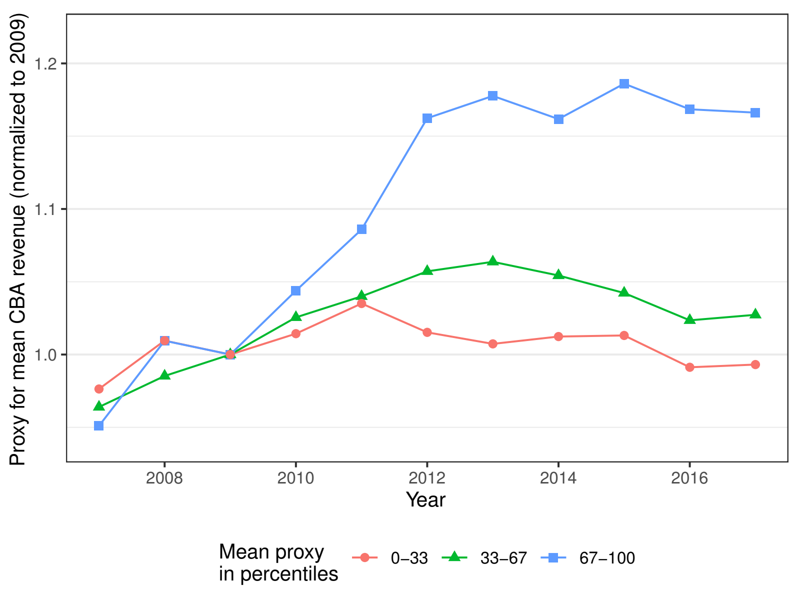
Notes: Data are from the National Institute of Statistics and Censuses (INDEC) and regional statistics offices. Panel (a) shows the evolution of the real gross domestic product (GDP), Panel (b) shows the yearly inflation rate constructed from alternative sources for the period 2007–2015, and Panel (c) shows the total exported value. The GDP is measured in constant 2004 argentinian pesos and normalized to 1 in 2004. The inflation rate is measured as the yearly percentage change in the consumer price index as of December. The total exported value is measured in millions of current US dollars.

Figure 2: Evolution of exporting shocks to firms and collective bargaining agreements

(a) Proxy for firm revenue



(b) Proxy for average CBA revenue

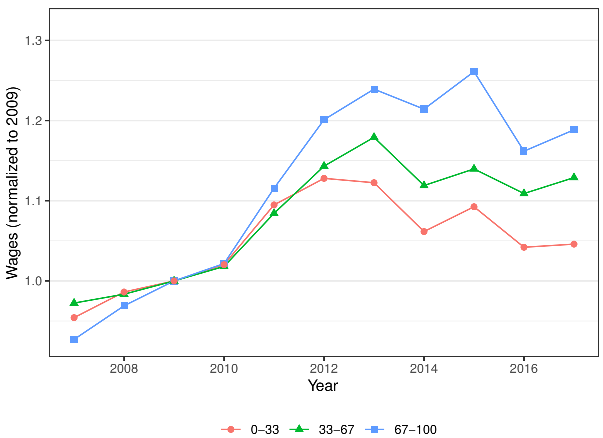


Notes: Data are constructed from a panel of firms that exported in 2011–2012. The figure illustrates the evolution of proxies for firm revenue z_{jt} in Panel (a) and proxies for average CBA revenue z_{ct} in Panel (b), for different levels of the firm and CBA shocks z_j and z_c. The firm shock z_j is defined as the difference between the 2012–2013 to the 2009–2010 valued-weighted average in world important demand across a firm's country-product exports. The CBA shock z_c is defined as the difference between the 2012–2013 to the 2009–2010 employment-weighted average of firm shocks across all exporting firms in a CBA. Each line depicts the average of the proxy (relative to 2008) for firms or CBAs in a given quartile of the distribution of the respective shock. The averages in Panel (b) are weighted by the number of firms in a given CBA.

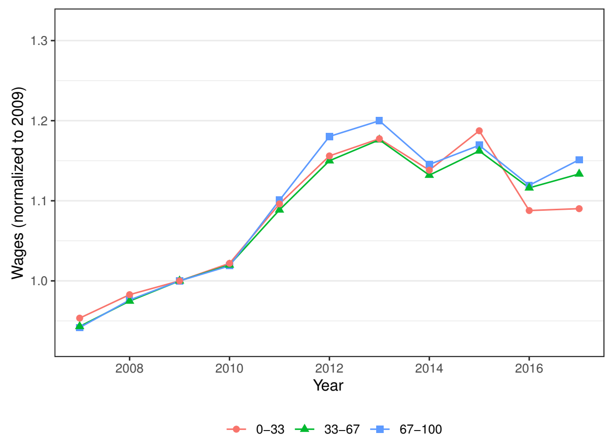
Figure 3: Evolution of wages and employment by level of CB unit and firm shock, baseline sample

Panel (a): Mean wages

CB shock

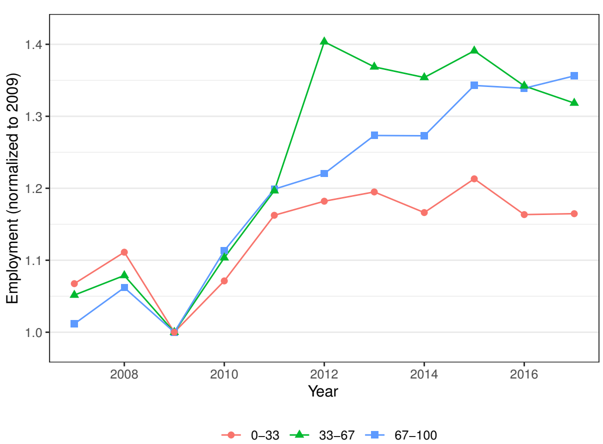


Firm shock



Panel (b): Employment

CBA shock



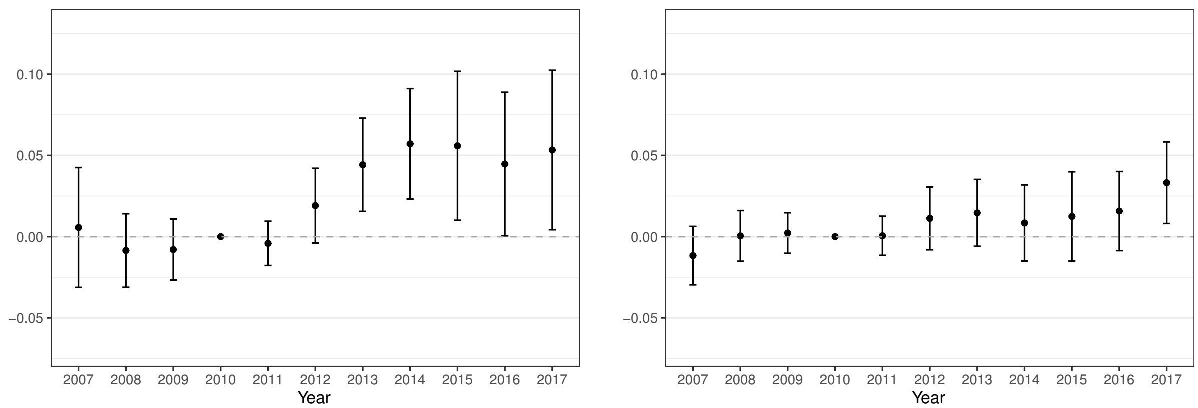
Firm shock

Notes: Data are from the baseline sample of exporting firms. The figure shows the average evolution of mean wages and employment for firms in different tertiles of the distribution of the CB shock (left column) and the firm shock (right column), relative to 2009. The firm shock is defined as the difference between the 2012–2013 to the 2009–2010 valued-weighted average in world important demand across a firm's country-product exports. The CB shock is defined as the difference between the 2012–2013 to the 2009–2010 employment-weighted average of firm shocks across all exporting firms in a CB imot.

Figure 4: Effect of exporting shocks on mean wages and employment

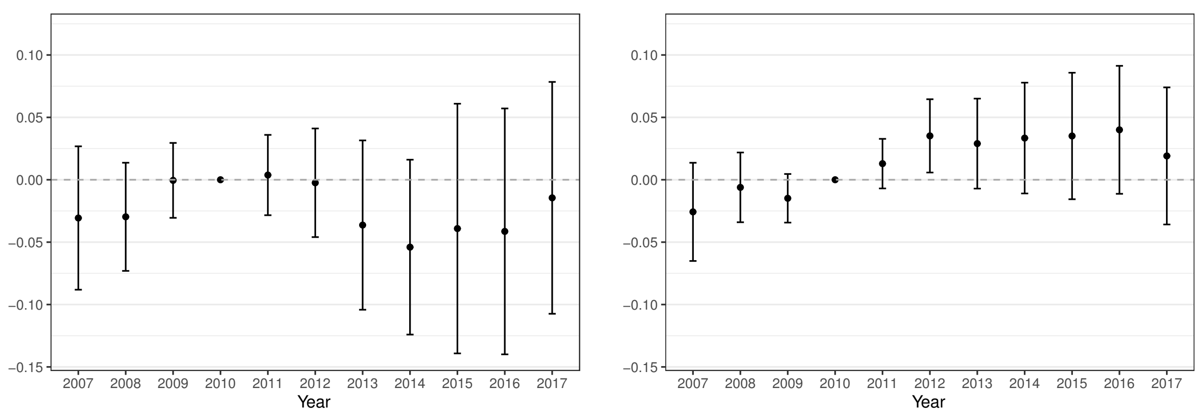
Panel (a): Log mean wages

CB shock | Firm shock



Panel (b): Log employment

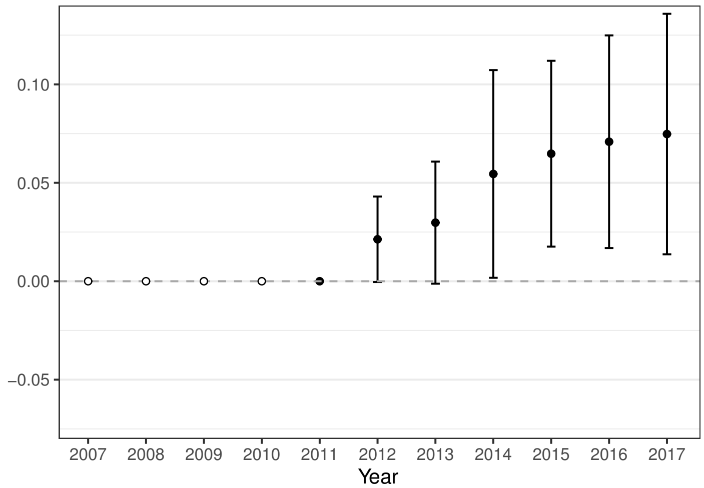
CB shock | Firm shock



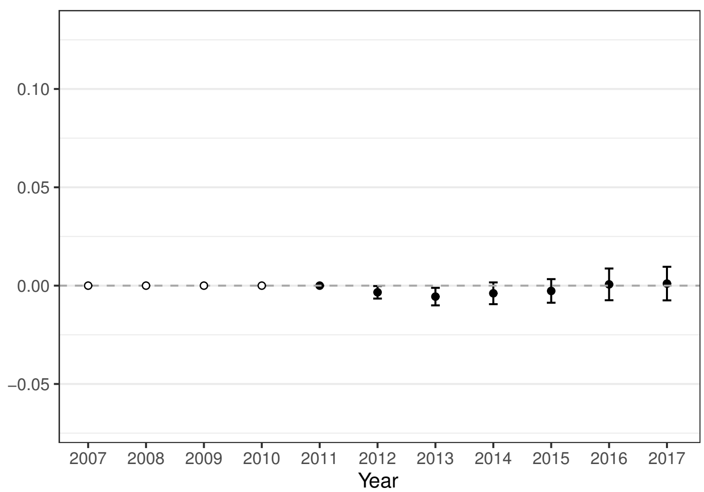
Notes: Data are from the baseline sample of exporting firms. The figure shows the dynamic effects of firm and CB shocks on log mean wages and log employment, interacting the shocks with year dummies and omitting the year 2010. The regression includes firm fixed effects, 4-digit economic sector by province by year fixed effects, firm controls, and a similar CB shock for the pre-period interacted with year dummies. Firm controls consist of a firm size indicator (categories 1-9, 10-24, 25-99, and 100-500) interacted with 2-digit sector and year and the pre-period share of workers in the main hiring modality interacted with year. Product-demand shocks are constructed from the average change in world import demand for a given country-product between 2009–2010 and 2012–2013. The firm shock is defined as the average product-demand shock, weighting by exposure via exports. The CB shock is defined as the average product-demand shock, weighting by the exposure via employment in exporting firms. Standard errors are clustered at the CB unit level for the CB shock variable, and at the firm level for the firm shock variable.

Figure 5: Effect of exporting shocks on log mean wage floors

CB shock



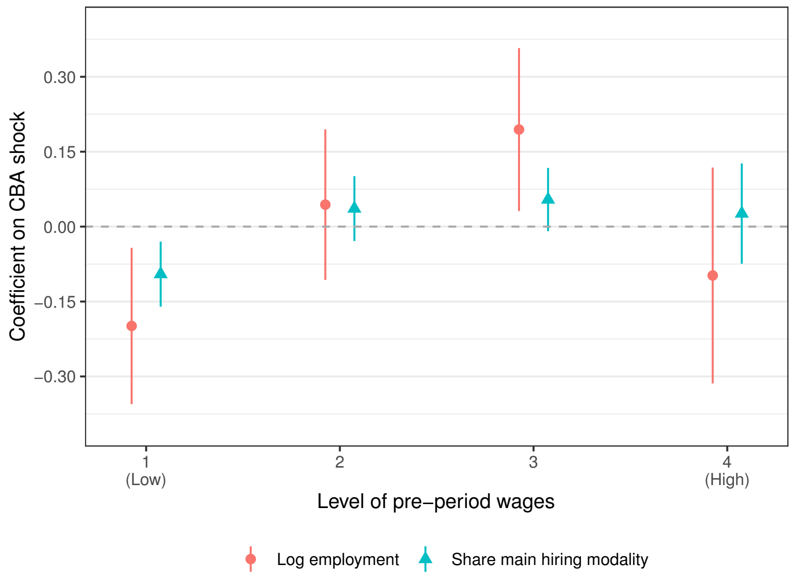
Firm shock



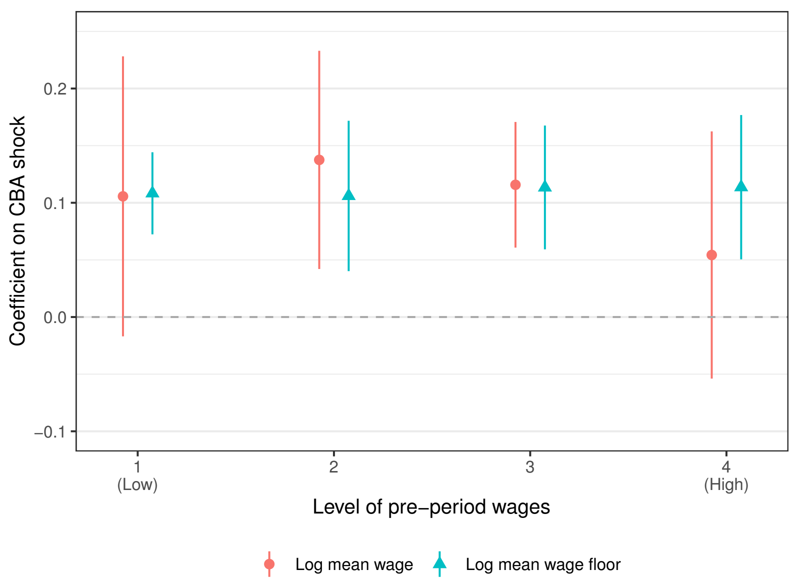
Notes: Data are from the baseline sample of exporting firms, including only firm-years for which wage floors are available. The figure shows the dynamic effects of firm and CB shocks on log employment, interacting the shocks with year dummies and omitting the year 2011, the first year with available wage floor data. The white dots indicate years for which data are not available. The regression includes firm fixed effects, 4-digit economic sector by province by year fixed effects, firm controls, and a similar CB shock for the pre-period interacted with year dummies. Firm controls consist of a firm size indicator (categories 1-9, 10-24, 25-99, and 100-500) interacted with 2-digit sector and year and the pre-period share of workers in the main hiring modality interacted with year. Product-demand shocks are constructed from the average change in world import demand for a given country-product between 2009–2010 and 2012–2013. The firm shock is defined as the average product-demand shock, weighting by exposure via exports. The CB shock is defined as the average product-demand shock, weighting by the exposure via employment in exporting firms. Standard errors are clustered at the CB unit level for the CB shock variable, and at the firm level for the firm shock variable.

Figure 6: Effect of exporting shocks to CB units on exporting, heterogeneity analysis

(a) Employment outcomes



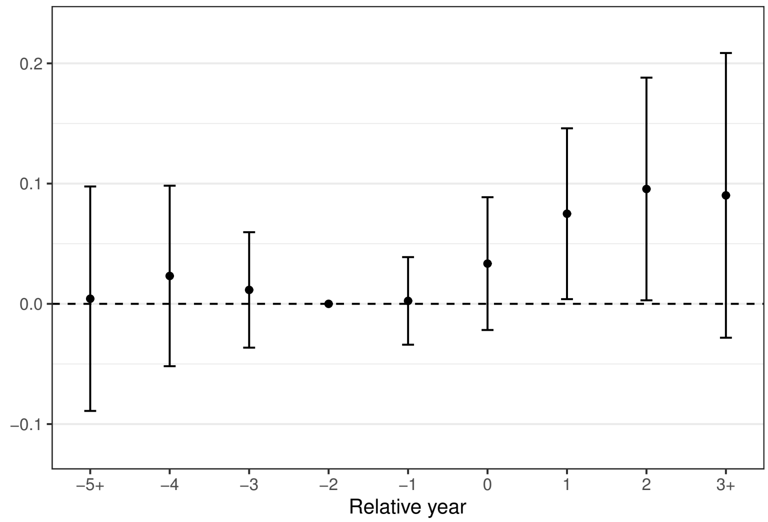
(b) Wage outcomes



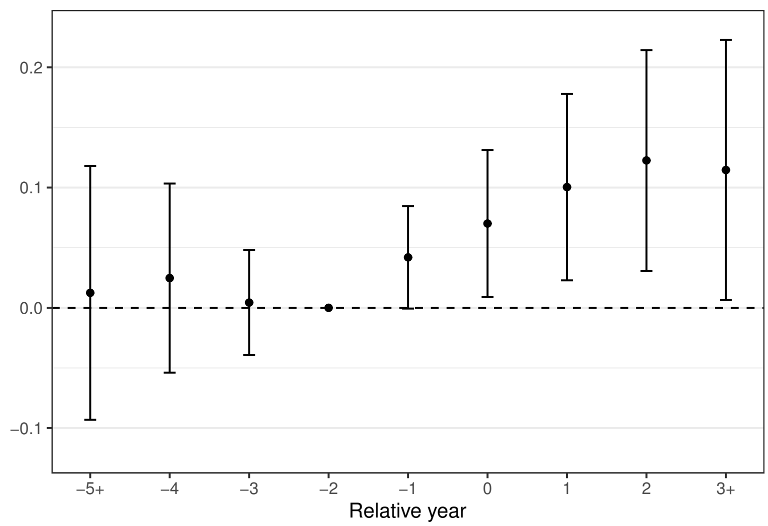
Notes: Data are from the baseline sample of exporting firms, excluding CB unit by province cells with less than 8 firms. The figure shows estimates of the effects of CBA shocks on a given outcome interacted with dummies for different quartiles of the pre-period level of wages (2007–2009), defined within CB unit by province cells. The top figure shows the effect of the place CBA shock on log mean wage and log mean wage floor, and the bottom figure shows the effect on the probabilty of being active, log employment, and the share of workers hired in the main hiring modality in the firm. Estimation is done using a difference-in-differences strategy as in Table 1, but excluding the firm shock and interacting the local labor market by year dummies with an exporter indicator. Standard errors are clustered at the CBA level.

Figure 7: Effect of firm shocks on firm's accounting, survey data

Log wage expenditures



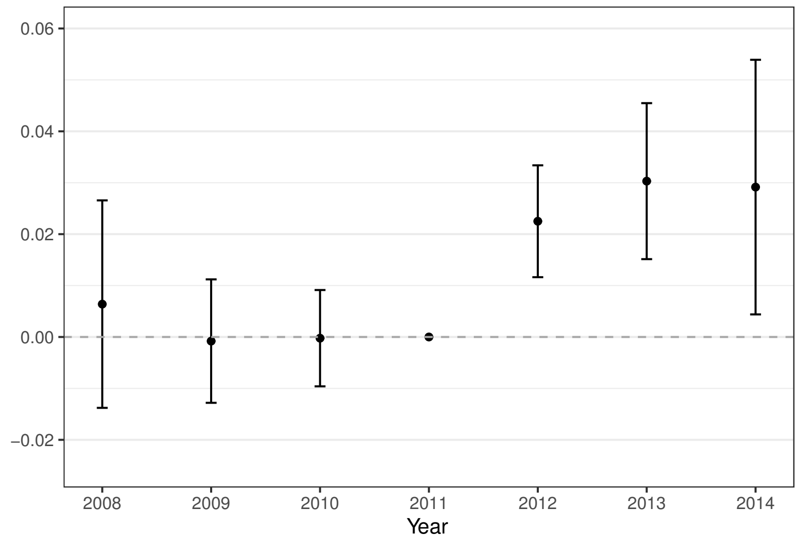
Log product market sales



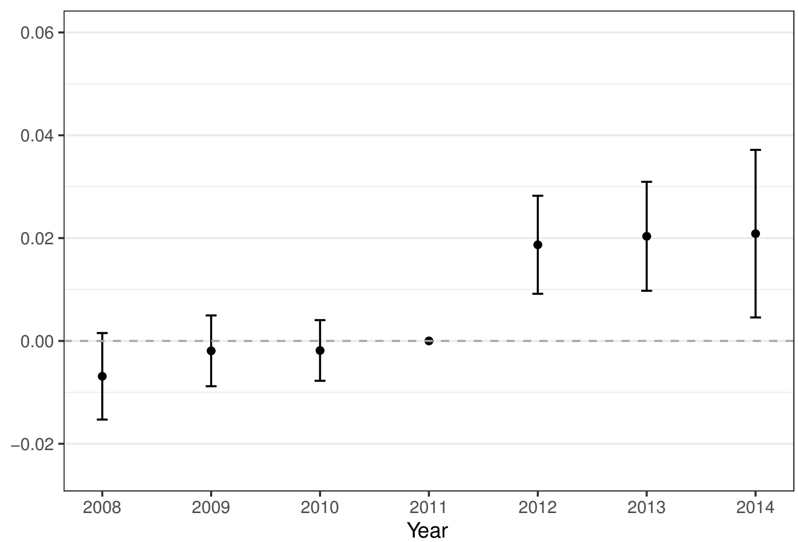
Notes: Data are from a sample of firms that exported in 2011–2012 that were surveyed in the first or second waves of the *Encuesta Nacional de Dinámica del Empleo y la Innovación* (ENDEI). The figure shows results of a firm shock on a surveyed firm accounting outcomes, using a panel event-study design. The firm shock is defined as the value-weighted average of log world import demand (WID) of the products the firm exports at baseline. The regressions include controls for firm fixed effects and 4-digit economic sector by province by year fixed effects. Standard errors are clustered at the firm level.

Figure 8: Effect of exporting shocks to CB units, worker-level DiD estimates

(a) Shock to firm's primary CB

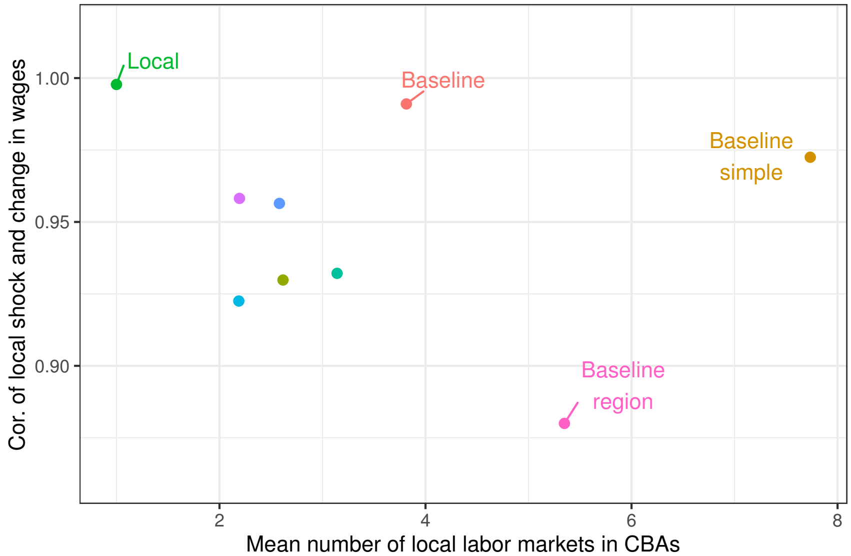


(b) Shock to worker's CB unit, controlling for firm unobserved heterogeneity



Notes: Data are a panel of workers that worked in exporting firms in 2011–2012 in all 2008, 2011, and 2014. The figures show estimates of the effect of CB shocks on mean monthly wage. The top figure estimates a difference-in-differences model using our main CB shock variable as treatment and includes controls for the firm shock, worker by firm ("match") fixed effects, 6-digit economic sector by province by year fixed effects, hiring modality by year fixed effects, and 2-digit economic sector by an indicator for whether the worker's CB is the primary CB unit in the firm by year fixed effects. The bottom figure estimates a difference-in-differences model as well, but instead uses the CB shock that is specific to each worker and controls for worker fixed effects and firm by year fixed effects. Both figures exclude "hierarchical" workers which are excluded from collective bargaining provisions. Standard errors are clustered at the CB unit level.

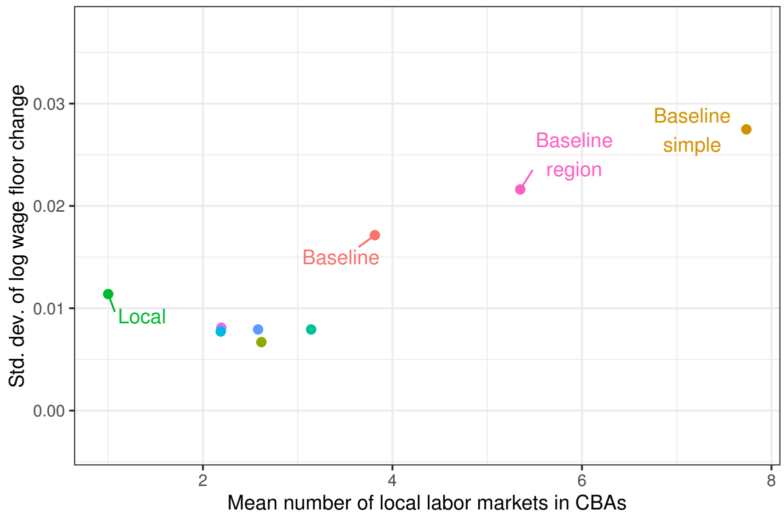
Figure 9: Centralization of bargaining and shock propagation



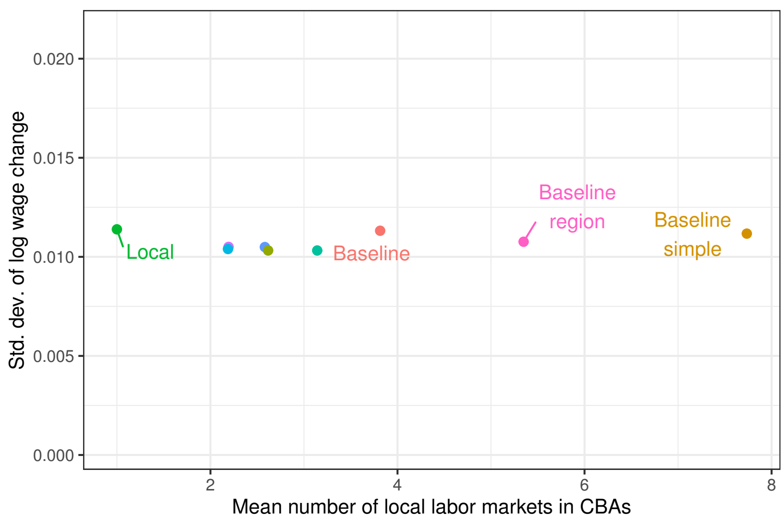
Notes: The figure shows the correlation between shocks and wages at the local labor market for CB networks with different levels of centralization of bargaining. The measure of centralization is the average number of local labor markets per CB unit. The correlation is computed using the model-generated data. The figure excludes local labor markets that correspond to the retail CBA at baseline and with less than 5% of employment in exporting firms.

Figure 10: Centralization of bargaining and shock propagation

(a) Wage floor



(b) Mean wage



Notes: The figure shows the variable of wages at the local labor market for CB networks with different levels of centralization of bargaining. The measure of centralization is the average number of local labor markets per CB unit. The measures of variability are the standard deviation of the wage floor and the mean wage, respectively. The figure excludes local labor markets that correspond to the retail CBA at baseline and with less than 5% of employment in exporting firms.

Table 1: Static difference-in-differences estimates

	Log mean wage	Log mean wage floor	Log wage cushion	Log employment	Sh. main modality	Firm exit
	(1)	(2)	(3)	(4)	(5)	(6)
CB shock	0.0482	0.0505	-0.0026	-0.0197	0.0145	-0.0060
	(0.0183)	(0.0197)	(0.0154)	(0.0353)	(0.0151)	(0.0085)
Firm shock	0.0173	-0.0026	0.0168	0.0388	0.0043	0.0002
	(0.0093)	(0.0024)	(0.0089)	(0.0194)	(0.0066)	(0.0054)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Local market-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes
Pre-period CB shock	Yes	Yes	Yes	Yes	Yes	Yes
Num. firms	7,601	7,331	7,331	7,601	7,601	7,601
Num. fixed effects	19,608	14,605	14,605	19,608	19,648	19,800
Num. observations	81,789	48,613	48,609	81,789	82,232	83,611
Adjusted R^2	0.8503	0.9275	0.8359	0.8991	0.6539	0.3627

Notes: Data are from the baseline sample of exporting firms. The table show regression coefficients on the firm and CB shocks variables interacted with an indicator for year greater than or equal to 2012. The regression includes firm fixed effects, 4-digit economic sector by province by year fixed effects, firm controls, and a similar CB shock for the pre-period interacted with year dummies. Firm controls consist of a firm size indicator (categories 1-9, 10-24, 25-99, and 100-500) interacted with 2-digit sector and year and the pre-period share of workers in the main hiring modality interacted with year. The firm shock is defined as the difference between the 2012–2013 to the 2009–2010 valued-weighted average in world important demand across a firm's country-product exports. The CB shock is defined as the difference between the 2012–2013 to the 2009–2010 employment-weighted average of firm shocks across all exporting firms in a CB unit. Standard errors are clustered at the CB level for the CB shock variable, and at the firm level for the firm shock variable.

Appendix

A Proofs for Theoretical Framework

Proof of Proposition 1. The Nash split equation is given by

$$\sum_{j\in\mathcal{J}} w_j\ell_j = \omega \sum_{j\in\mathcal{J}} \varphi_j f(\ell),$$

where the $w_j = \underline{w}$ and $\ell_j = \ell_j(\underline{w}, \varphi_j)$ for constrained firms and $w_j = w(\varphi_j)$ and $\ell_j = \ell_j(w_j)$ for unconstrained ones.

Let $\mathcal{J}^{\text{co}}$ be the non-empty set of constrained firms, and $\mathcal{J}^{\text{uco}} = \mathcal{J}\backslash\mathcal{J}^{\text{co}}$ the set of unconstrained firms. Assume that ω is fixed. Differentiating with respect to φ_j and $\underline{w}$, and reordering terms yields

$$\begin{aligned}\sum_{j\in\mathcal{J}^{\text{co}}} \left(\ell_j + \underline{w}\frac{d\ell}{dw_j} - \omega\varphi_j f_\ell \frac{d\ell_j}{dw}\right) d\underline{w} &= \omega \sum_{j\in\mathcal{J}} f(\ell_j) d\varphi_j \\ &+ \sum_{j\in\mathcal{J}^{\text{co}}} \left(\omega\varphi_j f_\ell - \underline{w}\right)\frac{d\ell_j}{d\varphi} d\varphi_j + \sum_{j\in\mathcal{J}^{\text{uco}}} \left(\varphi_j f_\ell \frac{d\ell_j}{dw} - \ell_j + w_j \frac{d\ell_j}{dw_j}\right)\frac{dw_j}{d\varphi_j} d\varphi_j \\ &+ \sum_{j\in\mathcal{J}^{\text{co}}} \left(\omega\varphi_j f_\ell - \underline{w}\right)\frac{d\ell_j}{d\varphi} d\varphi_j + \sum_{j\in\mathcal{J}^{\text{uco}}} \left(\varphi_j f_\ell \frac{d\ell_j}{dw} - \ell_j + w_j \frac{d\ell_j}{dw_j}\right)\frac{dw_j}{d\varphi_j} d\varphi_j.\end{aligned} \tag{A.1}$$

where $L = \sum_{j'\in\mathcal{J}} \ell_{j'}$ is aggregate employment in the CBA.

From the FOC of the firm problem we know that $\ell_j + w_j \frac{d\ell_j}{dw_j} = \varphi_j f_\ell \frac{d\ell_j}{dw_j}$ for all $j \in \mathcal{J}^{\text{uco}}$, and that $\underline{w} = \varphi_j f_\ell$ for all $j \in \mathcal{J}^{\text{co}}$. We will add and subtract terms to drop the terms involving f_ℓ. Note also that $d\underline{w} = \underline{w} d\ln\underline{w}$ and $d\varphi_j = \varphi_j d\ln\varphi_j$, and that we can also construct some elasticities by multiplying and diving by appropriate terms. This yields

$$\begin{aligned}\sum_{j\in\mathcal{J}^{\text{co}}} \underline{w}\ell_j\left(1 + (1-\omega)\eta_j\right) d\ln\underline{w} &= \omega\sum_{j\in\mathcal{J}} \varphi_j f(\ell_j) d\ln\varphi_j \\ &- (1-\omega)\sum_{j\in\mathcal{J}^{\text{co}}} \underline{w}\ell_j\rho_j^\ell d\ln\varphi_j - (1-\omega)\sum_{j\in\mathcal{J}^{\text{uco}}} w_j\ell_j\left(1+\eta_j\right)\rho_j^w d\varphi_j,\end{aligned}$$

where $\eta_j = \frac{d\ell_j}{dw}\frac{w}{\ell_j}$, $\rho_j^\ell = \frac{d\ell_j}{d\varphi}\frac{\varphi_j}{\ell_j}$, and $\rho_j^w = \frac{dw_j}{d\varphi_j}\frac{\varphi_j}{w_j}$ are elasticities. Let us now define the adjusted wage bill

$$\tilde{WB}^{\text{co}} = \sum_{j\in\mathcal{J}^{\text{co}}} \underline{w}\ell_j\left(1 + (1-\omega)\eta_j\right). \tag{A.2}$$

Using this definition, recalling that $R_j = \varphi_j f(\ell_j)$ and $WB_j = w_j\ell_j$, and dividing and multiplying appropriately to obtain shares, we can write

$$
\begin{aligned}
d \ln \underline{w} = {} & \frac{WB}{\tilde{WB}^{\text{co}}} \sum_{j \in \mathcal{J}} s_j^R d \ln \varphi_j \\
& - (1-\omega_c) \frac{WB}{\tilde{WB}^{\text{co}}} \left[\sum_{j \in \mathcal{J}^{\text{co}}} s_j^{WB} \rho_j^{\ell} d \ln \varphi_j - \sum_{j \in \mathcal{J}^{\text{uco}}} s_j^{WB} \left(1+\eta_j\right) \rho_j^{w} d\varphi_j \right].
\end{aligned}
$$

Defining the elasticity of the wage bill as $\iota_j = \rho_j^{\ell}$ for constrained firms and $\iota_j = \left(1+\eta_j\right)\rho_j^{w}$ for unconstrained firms, we can use the previous expression to obtain equation (4).

Now, if ω is not fixed, then (A.1) will have an extra term, namely

$$
\begin{aligned}
& R\left(\frac{d\omega}{d\underline{w}_c} + \sum_j \frac{d\omega}{d\varphi_j}\right) = \\
& \qquad R\omega(1-\beta) \left(\frac{d\left[\left(-\frac{d\Pi}{d\underline{w}} / \frac{dU}{d\underline{w}}\right)\right]}{d\underline{w}} + \sum_j \frac{d\left[\left(-\frac{d\Pi}{d\underline{w}} / \frac{dU}{d\underline{w}}\right)\right]}{d\varphi_j} \right).
\end{aligned}
$$

After the corresponding algebraic manipulations, the final expression in equation (4) can be obtained with an extra term that corresponds to the previous expression divided by $\tilde{WB}^{\text{co}}$.

□

B Details on Context and Data

B.1 Labor market institutions in Argentina

The Law of Labor Contracts (N° 20.744) sets the general standards for all labor relations. Above this base, a set of collective bargaining agreements (CBAs) establishes standards that are binding for subgroups of workers in different industries, occupations, and firms. Private-sector CBAs are governed by the regime in Law N° 14.250, first sanctioned in 1953. Different regimes regulate CBAs for government employees and educators. The CBAs are negotiated between unions and employer associations, and sometimes they are adhered by other unions that did not participate in the negotiation directly. The government acts as a mediator and legal validator of the agreements. The terms agreed upon in CBAs establish are taking as minimum standards for workers that individual firms cannot undercut.

Types of unions. In Argentina, there is freedom of association, which enables any worker group to form a union. Unions exist in 3 legal forms: basic unions (*sindicatos*), which directly represent workers, are the most common; federations (*federaciones*), which are groups of unions; and confederations (*confederaciones*), which can include federations and basic unions.

However, only one union per "area of representation" is allowed to negotiate collective agreements. The government grants bargaining privileges to unions that meet certain requirements, such as being the union with more affiliates among the workers that they aim to represent.[1]

It is not uncommon to find unions with bargaining privileges that simply adhere to existing CBAs. An example is the retail sector (*comercio*). The CBA with the largest coverage in Argentina is the 0130/75, which was signed by the federation of trade unions, and it is adhered by many regional basic unions. Furthermore, a single union can participate in multiple CBAs and a single CBA can have multiple adhering unions. In the paper I focus on the role of collective bargaining units, abstracting from these complexities.

Areas of representation. An area of representation can be determined by industry, occupation, geographical location, or even a single employer, and is formally defined when the government grants bargaining privileges to a union that request them. Areas of representation effectively defined the structure of collective bargaining units, and thus the CB networks. The government has the authority to change these areas by granting or revoking bargaining privileges to unions for particular sectors or regions. However, areas of representation have been stable in the recent past.

CBAs, CBA alterations, and the negotiation process. A union with bargaining privileges and an employer association will typically negotiate a comprehensive CBA that outlines labor regulations applicable to the workers and firms they represent. I refer to these as "master CBAs" or simply CBAs, when the context is clear. Procedural rules for the negotiation process, established by law, define protocols for unions to formally request meetings with employers, facilitate information exchange (e.g., employers providing details about labor costs and organizational structures), among other considerations.[2] The use of strikes, as well as the procedure in case of employer crisis, is regulated by law as well. If an agreement is not reached, the government can issue an arbitral award to determine the regulations for the labor contracts of the involved workers.

Once a negotiation concludes, the resulting agreement is legally validated by the Ministry of Labor in a process termed *homologación*. The government archives these master CBAs under unique codes, which align with the CBA codes in my dataset. A master CBA may be modified by either a new master CBA that supersedes it,[3] or a "CBA alteration" that simply updates some provisions within it.[4] CBA alterations act as amendments to the master CBA. They typically relate to updates in wage scales, although they may also entail modifications in other provisions.

The dynamics of negotiations. Appendix Figure 1 shows the dynamics of collective negotiations in the same period. After a period of low activity in the 90s, the number of negotiations

[1]Unions that are registered but do not have bargaining privileges are known as *sindicatos simplemente inscriptos* (roughly, "unions simply registered"), while those with privileges are *sindicatos con personería gremial* ("unions with legal recognition"). The criteria for assigning *personería gremial* to unions are outlined in Law N° 23.551.

[2]The procedural rules for collective bargaining are established in Law N° 23.546.

[3]If the CBA is completely revised the code of the CBA in the data changes as well. I reviewed these cases so that a constant code appears in my data for the same bargaining unit.

[4]CBAs do not expire. This characteristic, known as "ultra-activity," is common in many countries.

reignited in the early 2000s.[5] The recovery from the 2001-2002 crisis triggered government interventions affecting private sector wages, such as minimum wage increases and even wage supplements by decree. These developments revitalized the negotiations, which at first incorporated these provisions into existing CBAs. The new ruling party, elected in 2003, introduced legislation that further encouraged negotiations, resulting in new master CBAs, galvanizing unions that had not negotiated in many years into signing new CBAs. These factors account for the peak of 150 new master CBAs signed in 2006 (Panel a). By 2014, 52% of active master CBAs had been signed in 2003 or later (Pontoni and Trajtemberg 2017). However, soaring inflation since 2007 prompted unions and employers to meet nearly annually to revise wages via CBA alterations. Panel (b) shows a large increase in alterations that persisted throughout the period.[6] Panel (c) shows that the share of CBA alterations that mention wage issues increased by 25% between 2009 and 2018.

B.2 Main labor market data

The primary source of information on the formal labor market is Argentina's matched employer-employee dataset. The tax authority collects this data for maintaining social security records, under a system known as *Sistema Integrado Previsional Argentino* (SIPA). I have gained access to a version of this data maintained by the Ministry of Labor (Ministerio de Trabajo, Empleo y Seguridad Social 2022b), covering the years 2007 through 2020. The data contain firm and worker identifiers, as well as information on worker compensation in each month, and worker and firm characteristics.

I use a second administrative dataset to obtain additional information on labor relations (Ministerio de Trabajo, Empleo y Seguridad Social 2022a). This dataset, collected also by the tax authority under a system known as *Simplificación Registral*, is constructed from employer's online declarations during hiring or termination of workers. The system was introduced progressively since 2008. The goal of the system was to simplify the process of registering workers and to collect useful information on labor relations that could be used, for example, to allocate government programs. Appendix Table 2 lists the size thresholds that determined whether firms were required or had the option to enter the system at different times. The idea was to accommodate larger firms who might need more time to adjust to the new system. The dataset contains the same firm and worker identifiers as SIPA, the CBA code, the worker's category within the CBA, and an occupation code.[7]

[5] The 90s negotiations took place in a context of pro-market reforms that weakened traditional unions. See Palomino and Trajtemberg (2006) for a discussion of the dynamics of negotiations in 1991–2006.

[6] The 2017 dip in the number of CBA alterations can also be attributed to inflation-related developments. Encouraged by the government, some CBAs introduced a "trigger clause" that would automatically update wages in case of unanticipated inflation, thus reducing the need to negotiate.

[7] Other variables in the system include family relationships of workers, and the precise geographical location of firms and workers.

B.3 Other data sources

Survey data on firms. To study how a firm's finances respond to economic shocks, I use survey data from a national business survey. This survey, known as *Encuesta Nacional de Dinámica de Empleo e Innovación* (ENDEI), was conducted jointly by the Ministry of Labor and the Ministry of Science and Technology. Conducted in two rounds in 2012 and 2016, the survey asks about the firm's situation in regard to innovation in the 3 previous years. Fortunately, the survey also collected information on self-declared revenue and expenditures. Some firms were sampled twice, and are thus observed for 6 years. I identify 1,987 firms that participated in the survey at least once and exported in 2011–2012, which accounts for 22% of the firms in my primary estimation sample.

International trade data. I collected data from the publicly available BACI-CEPII dataset (Gaulier and Zignago 2010), which contains yearly trade follows between any pair of countries in each 6-digit product from the Harmonized System (HS) of product classification. In particular, I use the data coded with the 2007 version of the HS system, which covers the period 2007–2020. I use the HS code to match the BACI-CEPII data to the firm-level data.

I also obtained administrative data from Argentinian customs (*Dirección General de Aduanas*) which details the value exported to each country and product for every Argentinian firm. As a member of Mercosur, Argentina's product classification system is based on the *Nomenclatura Común del Mercosur* (NCM), which is an 8-digit code that is compatible with the HS. Using concordance tables from Liao et al. (2020), I convert NCM codes into 6-digit 2007 HS codes.[8] I use names to match country codes between the Customs data and BACI-CEPII.[9] I then aggregate the firm-level trade data to the 2007 HS and country level.

In here there should be a paragraph discussing the distribution of number of country-products exported per firm and CBA. I need to go back to the admin data to compute these numbers.

B.4 Imputation of CBA codes

Cleaning CBA codes at worker-firm level. Given the progressive introduction of *Simplificación Registral*, some information for workers is missing, including the CBA code. Additionally, the variable sometimes shows an outdated CBA code for collective bargaining units that signed a new master CBA. To increase the number of workers with a CBA code and update the codes I do the following.

First, in the early years of the system most workers are observed by their termination date only. I use this information to fill the declared CBA code backwards, which increases coverage

[8] To convert codes I proceed as follows. First, I convert NCM 8-digit to NCM 6-digit by keeping the first 6 digits. These 6 digits directly correspond to the HS, although not necessarily the 2007 version. I then convert codes in different years to HS 6-digit version 2007 using the appropriate concordance table. I impute a handful of codes that are not present in the concordance manually.

[9] This results in some missing values as the customs data contains a few country codes that are coded as "indeterminate."

quite a bit for 2008 through 2010. Second, I impute the CBA code to workers with a missing code in a firm-year cell if a single code is observed. If a single CBA code is observed in increasingly large cells (such as firm-occupation, 6-digit ISIC-postal code, and occupation-postal code), I impute that code to workers with a missing code in that cell. Finally, I update the CBA codes forward to take into account updates to master CBAs that result in a new code. To do so, I scraped data from an online search engine of CBAs constructed by the Ministry of Labor. The search engine tells the user whether a master CBA updates a previous one. Results were manually reviewed to ensure that the information was correct.

Appendix Figure 2 shows the share of workers in the employer-employee dataset with a non-missing CBA code in the raw data and after the imputation described below. The imputation increases coverage significantly. The most significant steps in the imputation are the backwards filling, which raises coverage in the yearly years, and the imputation using firm-year cells, which increases coverage by around 13% after 2010.

Defining a primary CBA for each firm. For firms employing workers across multiple CBAs, I define the primary CBA as the modal CBA code. If a firm does not have any workers associated with a CBA code, I assign the most frequent CBA code in the postal code and 4-digit economic sector. A few postal codes and 4-digit sector cells do not have any worker with a declared CBA code. In such cases I use wider cells defined by province and 4-digit economic sector. About 25% of codes across the economy are imputed. Among firms assigned a non-imputed code, the average share of workers with the primary CBA code is 97%.

C Computation of Wage Floors

The data lacks information on the wage floors set by the CBAs. I therefore use the distribution of wages within a CBA, worker category, CBA-region, and month to infer the wage floors.[10] I then smooth the resulting time series of wage floors to reduce noise.

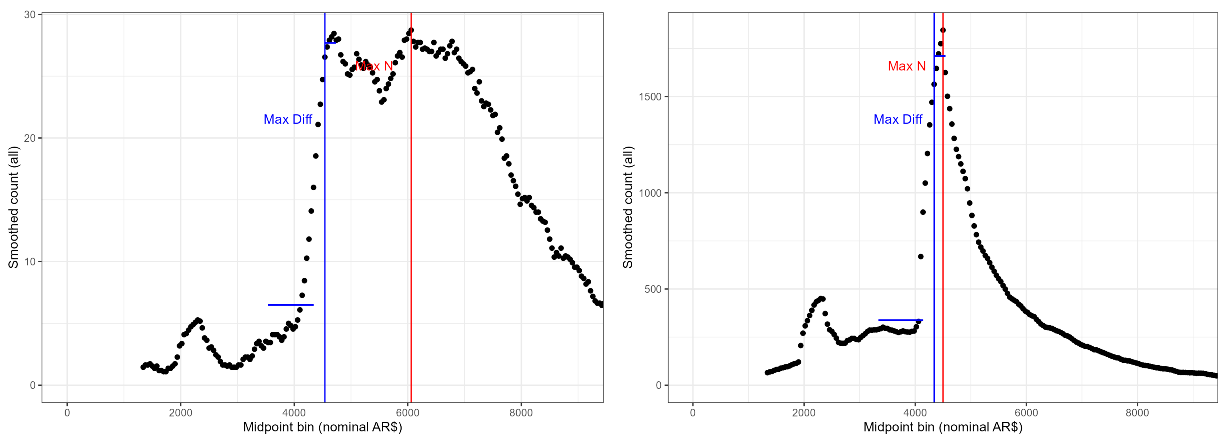
Figure C.1 shows the distribution of wages within a CBA, category, CBA region, and month. I use workers declared in the main hiring modality and exclude the first and last month of a spell as well as the months of June and December, as these months correspond to the 13th-month salary payments. We observe a clear bunching of wages at the wage floor. There is a significant mass of workers earning below the wage floor, which is to be expected as we do not control for hours worked and simply observe the total monthly wage received by the worker.[11] We also observe a smaller bunching point at around half the wage floor, which corresponds to workers that actually work part-time.

[10] Card and Cardoso (2022) observe wage floors but not the occupation category of workers. They rely on a lengthy matching process of CBA categories to occupations in the administrative data to assign wage floors to workers.

[11] Some reasons people may earn less than the wage floor are: workers are declared in the main hiring modality but are actually working part-time, workers miss some days in a month, workers are actually on vacation and did not receive the usual pay supplement for attendance.

The goal is to identify the bunching point. One possible way is to simply pick the mode of the distribution. However, as shown by the left panel of Appendix Figure C.1, the mode may be higher than the wage floor. A second option is to pick the maximum difference between a 20-bin average and the subsequent 5-bin average, trying to detect the point at which the distribution increases more rapidly. This is the preferred approach as it seems to capture the actual wage floor in a variety of cases.

Appendix Figure C.1: Illustration of the distribution of wages within a CBA, category, CBA region in January 2012



Notes: The figures show the distribution of wages within a CBA, category, CBA region, and month. The bins are equal to 20 pesos in 2012, but change with the inflation rate in subsequent years. The bins were smoothed using a moving average with a window of 5 bins at each side. The blue line shows the "maximum difference" between a 20-bin average with respect to the subsequent 5-bin average. The red line shows the mode of the distribution.

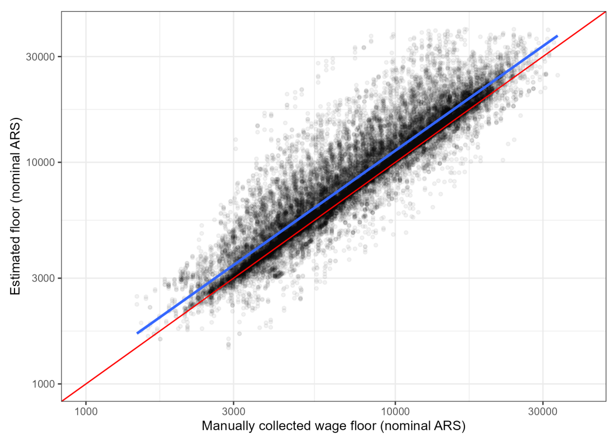
Now, after identifying the wage floors, I end up with a monthly time series of wage floors for each CBA, category, and CBA region cell. I start by dropping cells that appear for less than 3.5 years. I also drop categories that show an "unstable" behavior, i.e., for which the wage floor decreases for a period of time and then increases again. These restrictions attempt to drop the noisy CBAs with small samples. Finally, I smooth the time series of wage floors using a fixed-effects model that imposes that log wage floors are a linear function of CBA by category by CBA region fixed effects and CBA region by month fixed effects. The structure of most contracts is such that the relative difference between categories is constant over time and all wage floors increase at the same rate. The fixed-effects model captures this structure, reducing the noise in the data. I conclude by smoothing each series with a 1-month moving average.

Appendix Figure C.2 shows a comparison between manually collected wage floors and the wage floors inferred from the distribution of wages. The manual collection is challenging as it requires reading the actual agreements, which are usually in PDF format and do not follow a consistent structure over time. Furthermore, it is common for agreements to include non-compensatory payments, or one-time payments, that are hard to identify in the PDFs. Panel (a) shows that the levels of the wage floors are similar, with the data-inferred wage floors being slightly higher (suggesting that the manual collection may be missing some non-compensatory payments). The comparison is similar when using the average wage floor in each semester, as shown in Panel (b). Finally, Panel (c) compares the changes in the wage floors in each semester. We observe that the wage floors on average line up fairly well. However, the manually collected wage floors exhibit a higher volatility than the data-inferred wage floors. This is likely due to the fact that the manual collection is missing some form of compensation, and as a result we have a few large jumps in them. For example, if the manual collection missed one update of the wage scales, then the collected wage floor would appear to jump by a larger amount in the next update.

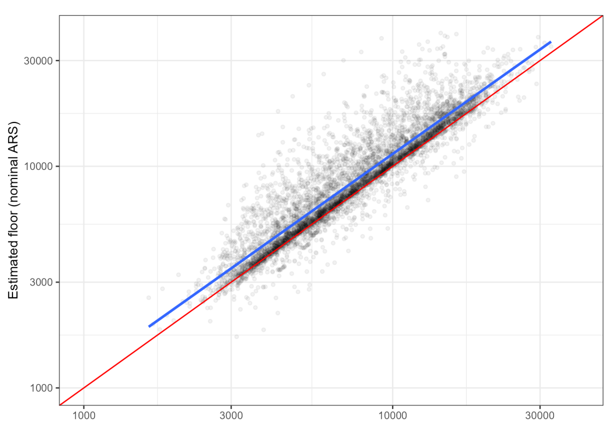
Overall, the manually collected wage floors serve as a decent approximation to the actual wage floors set by the CBAs. I acknowledge that they may be noisy. However, this noise is likely uncorrelated with the CBA shocks, and therefore should not affect the empirical results of the paper.

Appendix Figure C.2: Validation of wage floors with manually collected wage floor data

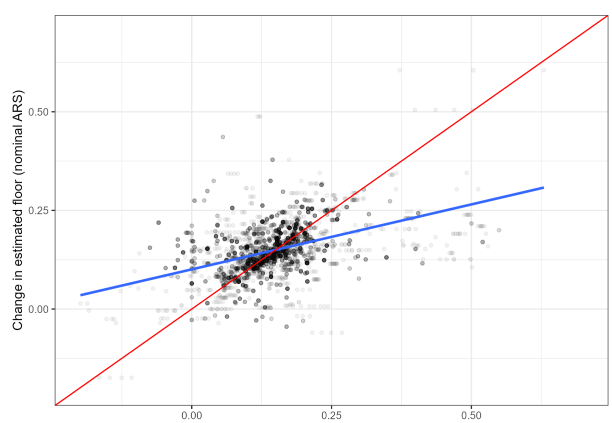
(a) Monthly comparison



(b) Semester average comparison



(c) Changes in semester average



Notes: The figures show a comparison between the manually collected wage floors and the wage floors inferred from the distribution of wages. The top panel shows a monthly comparison of the wage floors. The bottom left panel shows a similar comparison but using the average wage floor in each semester. The bottom right panel shows the change in the average wage floor in each semester.

D Shift-share Identification with Two Treatments

In this section I will show that identification of equation (5) can be cast in terms of Borusyak et al. (2022b). For this section I simplify the model in (5) to two time-periods, a "pre" and a "post," and assume that there is a single intercept for all firms. The reasoning would go through with more time periods and local labor market intercepts, but the notation would be more cumbersome. The model in first differences is

$$\Delta y_j = \delta + \beta_1 z_{j1} + \beta_2 z_{j2} + \varepsilon_j, \tag{D.1}$$

where z_{j1} and z_{j2} correspond to the firm and CB shocks, respectively, and can be written as

$$z_{jn} = \sum_{p \in \mathcal{P}} s_{jpn} f_p, \quad n \in \{1, 2\}.$$

The goal is to show that the moment conditions that identify the parameters β_1 and β_2 in (D.1) can be cast in terms of an analogous shock-level regression to which the quasi-randomness assumption can be applied. Let $\mathcal{J}$ be the set of firms. The full-data moment conditions are

$$\mathbb{E}\left[\frac{1}{|\mathcal{J}|}\sum_{j' \in \mathcal{J}} \left(\Delta y_{j'} - \delta - \beta_1 z_{j'1} - \beta_2 z_{j'2}\right)\right] = 0$$

$$\mathbb{E}\left[\frac{1}{|\mathcal{J}|}\sum_{j' \in \mathcal{J}} z_{j'1}\left(\Delta y_{j'} - \delta - \beta_1 z_{j'1} - \beta_2 z_{j'2}\right)\right] = 0$$

$$\mathbb{E}\left[\frac{1}{|\mathcal{J}|}\sum_{j' \in \mathcal{J}} z_{j'2}\left(\Delta y_{j'} - \delta - \beta_1 z_{j'1} - \beta_2 z_{j'2}\right)\right] = 0.$$

Partial out the intercepts by demeaning, so that $\Delta\tilde{y}_j = \Delta y_j - (1/|\mathcal{J}|)\sum_{j' \in \mathcal{J}} \Delta y_{j'}$ and, for each $n \in \{1, 2\}$, $\tilde{z}_{jn} = z_{jn} - (1/|\mathcal{J}|)\sum_{j' \in \mathcal{J}} z_{j'n} = \sum_{p \in \mathcal{P}} \tilde{s}_{jpn} f_p$ with $\tilde{s}_{jpn} = s_{jpn} - (1/|\mathcal{J}|)\sum_{j' \in \mathcal{J}} s_{j'pn}$. Then the moment conditions can be written as

$$\mathbb{E}\left[\frac{1}{|\mathcal{J}|}\sum_{j' \in \mathcal{J}} \tilde{z}_{j'1}\left(\Delta\tilde{y}_{j'} - \beta_1 \tilde{z}_{j'1} - \beta_2 \tilde{z}_{j'2}\right)\right] = 0$$

$$\mathbb{E}\left[\frac{1}{|\mathcal{J}|}\sum_{j' \in \mathcal{J}} \tilde{z}_{j'2}\left(\Delta\tilde{y}_{j'} - \beta_1 \tilde{z}_{j'1} - \beta_2 \tilde{z}_{j'2}\right)\right] = 0.$$

Following Borusyak et al. (2022b), each of the moment conditions can be equivalently written as, for $n \in \{1,2\}$,

$$\begin{aligned}
0 &= \mathbb{E}\left[\frac{1}{|\mathcal{J}|}\sum_{j'\in\mathcal{J}} \tilde{z}_{j'n}\left(\Delta\tilde{y}_{j'} - \beta_1\tilde{z}_{j'1} - \beta_2\tilde{z}_{j'2}\right)\right] \\
&= \mathbb{E}\left[\frac{1}{|\mathcal{J}|}\sum_{j'\in\mathcal{J}} \left(\sum_{p\in\mathcal{P}} \tilde{s}_{jpn} f_p\right)\left(\Delta\tilde{y}_{j'} - \beta_1\tilde{z}_{j'1} - \beta_2\tilde{z}_{j'2}\right)\right] \\
&= \mathbb{E}\left[\sum_{p\in\mathcal{P}} f_p \frac{1}{|\mathcal{J}|}\sum_{j'\in\mathcal{J}} \tilde{s}_{jpn}\left(\Delta\tilde{y}_{j'} - \beta_1\tilde{z}_{j'1} - \beta_2\tilde{z}_{j'2}\right)\right] \\
&= \mathbb{E}\left[\sum_{p\in\mathcal{P}} f_p r_{pn}\left(\beta_1,\beta_2\right)\right],
\end{aligned}$$

where $r_{pn}\left(\beta_1,\beta_2\right) = \left(1/|\mathcal{J}|\right)\sum_{j'\in\mathcal{J}} \tilde{s}_{j'pn}\left(\Delta\tilde{y}_{j'} - \beta_1\tilde{z}_{j'1} - \beta_2\tilde{z}_{j'2}\right)$ is an average residual for each country-product.

This is a country-product-level GMM problem, so under the assumption that shocks are quasi-randomly assigned these moment conditions would identify β_1 and β_2. We see that the logic of Borusyak et al. (2022b) applies to the case of two shift-share variables that are functions of the same set of country-product shocks. This case extends the results in Appendix A.10 of Borusyak et al. (2022b), which considers the case of multiple shift-share variables that use the same weights but different country-product shocks.

E A panel event-study design

The DiD strategy compares changes in outcomes between firms that received different treatment doses between 2010 and 2013. Since firms and CBAs may experience changes in their product demand at different times, the DiD strategy may drop useful variation. I introduce a panel event-study design to address this issue. This approach allows me to construct event-study plots to examine the impact on outcomes even if they were not observed throughout the entire period.

Consider the following panel model:

$$y_{jt} = \theta z_{c(j)t} + \beta z_{jt} + \alpha_j + \delta_{\ell(j)t} + X'_{jt}\psi + \varepsilon_{jt}$$

where variables are defined as in 5. This model imposes that only the period-t shocks affect the outcome. However, it is possible that the effect of the shock takes time to fully materialize. To account for this, I follow Freyaldenhoven et al. (forthcoming) and add a specific transformation of the leads and lags of the shock variables into the model:

$$
\begin{aligned}
y_{jt} = {} & \beta_{-\underline{R}-1}\left(-z_{j,t+\underline{R}}\right) + \sum_{r\in\mathcal{R}} \beta_k \Delta z_{j,t-r} + \beta_{\overline{R}}\left(z_{j,t-\overline{R}}\right) \\
& + \theta_{-\underline{R}-1}\left(-z_{c(j),t+\underline{R}}\right) + \sum_{r\in\mathcal{R}} \theta_k \Delta z_{c(j),t-r} + \theta_{\overline{R}}\left(z_{c(j),t-\overline{R}}\right) \\
& + \gamma_t S_c + X'_{jt}\psi + \alpha_j + \delta_{\ell(j)t} + \varepsilon_{jt}.
\end{aligned} \tag{E.1}
$$

In this equation $\mathcal{R}$ is a set of "relative years" running from $-\underline{R}$ to $\overline{R}-1$. Given that the end-point values and the first-differences of each z sum to 0, a normalization is required, enabling the creation of the familiar event-study plot.

The parameters of this model are identified by different comparisons relative to (5). The outcome at each year t is affected by a set of event-study coefficients of each treatment, which are identified by the conditional covariance of the period-t change in outcome to the period-t change in the treatment, relative to the normalized period. Future values of the treatment (i.e., forward values up to $\overline{R}$ years) pin down the pre-period coefficients. If there is no correlation between future shocks and current outcomes, then these coefficients should be zero.[12] Similarly, past values of the z's (i.e., lagged values up to $\underline{R}$ years) identify the dynamic effects of the treatment.

I set $\underline{R} = 6$ and $\overline{R} = 4$. Given that my international trade data runs from 2007 and 2020, I use only the years 2011 to 2014 in estimation when including the complete set of event-study variables.[13] A second decision concerns the period to normalize to 0. Considering that the treatment variables exhibit some AR(1) autocorrelation, I normalize the relative year -2 for both sets of event-study variables.

F Details on Structural Model

F.1 Derivations

F.1.1 Labor supply: supply to the firm decision

The cdf and pdf of a Fréchet distribution with shape η, scale equal to one and location equal to zero are given by

$$F(\xi) = e^{-\xi^{-\eta}}, \quad f(\xi) = \eta\xi^{-\eta-1}e^{-\xi^{-\eta}}.$$

Let Ω_r be the set of firms operating in region r. The share of formal-sector workers in region

[12] Contrast this with the DiD model where zero pre-trends for those treated at t result from no correlation between *current* shocks and *past* outcomes.

[13] For 2011 the earliest lead used is $2011 - 4 = 2007$. For 2014 the latest lag used is $2014 + 6 = 2020$.

r who optimally choose firm j is given by

$$\begin{aligned}
\ell(j) &= \int_0^1 \Pr\left(V_{ir}(j) \geq V_{ir}(j')\forall j' \neq j\right) di \\
&= \int_0^1 \int_0^\infty f(\xi(j)) \prod_{j' \in \Omega_r \backslash \{j\}} F\left(\frac{w(j)A_{k1(j)}\xi(j)}{w(j')A_{k1(j')}}\right) d\xi(j) di \\
&= \int_0^1 \int_0^\infty f(\xi(j)) \prod_{j' \in \Omega_r \backslash \{j\}} F\left(\frac{w(j)A_{k1(j)}\xi(j)}{w(j')A_{k1(j')}}\right) d\xi(j) di \\
&= \int_0^1 \int_0^\infty \eta\xi(j)^{-\eta-1}e^{-\xi(j)^{-\eta}} \prod_{j' \in \Omega_r \backslash \{j\}} e^{-\left(\frac{w(j)A_{k1(j)}\xi(j)}{w(j')A_{k1(j')}}\right)^{-\eta}} d\xi(j) di \\
&= \int_0^1 \int_0^\infty \eta\xi(j)^{-\eta-1}e^{\int_{j' \in \Omega_r} -\left(\frac{w(j)A_{k1(j)}\xi(j)}{w(j')A_{k1(j')}}\right)^{-\eta} dj'} d\xi(j) di \\
&= \int_0^1 \int_0^\infty \eta\xi(j)^{-\eta-1}e^{-\left(w(j)A_{k1(j)}\xi(j)\right)^{-\eta}} e^{\int_{j' \in \Omega_r}\left(w(j')A_{k1(j')}\right)^{\eta} dj'} d\xi(j) di.
\end{aligned}$$

Defining $s = \frac{\left[\int_{j' \in \Omega_r}\left(w(j')A_{k1(j')}\right)^{\eta} dj'\right]^{1/\eta}}{w(j)A_{k1(j)}}$ we can rewrite as

$$\ell(j) = \int_0^1 \int_0^\infty \eta\xi(j)^{-\eta-1}e^{-\left(\frac{\xi(j)}{s}\right)^{-\eta}} d\xi(j) di,$$

and further manipulations yield

$$\ell(j) = s^{-\eta} \int_0^1 \int_0^\infty \frac{\eta}{s}\left(\frac{\xi(j)}{s}\right)^{-\eta-1} e^{-\left(\frac{\xi(j)}{s}\right)^{-\eta}} d\xi(j) di,$$

Note that, as workers are homogeneous, the integral over i is irrelevant. Also, the expression inside the integrals is the pdf of a Fréchet distribution with shape η and scale s. Thus, the double integral above equals 1, and we have

$$\ell(j) = \left(\frac{w(j)A_{k1(j)}}{\int_{j' \in \Omega_r}\left(w(j')A_{k1(j')}\right)^{\eta} dj'}\right)^{\eta}.$$

The expression for expected utility can be obtained following similar steps. See Parente (2022, Appendix D).

F.1.2 Labor supply: Formal employment decision

Derivations are available in Ahlfeldt et al. (2022, Appendix D.2.1).

F.1.3 Labor demand: solution to firm problem

For *unconstrained* firms the solution to the firm's problem is

$$w(\varphi) = \left(\frac{\eta}{\eta+1}\right)\varphi, \quad \ell(\varphi) = W_r^{-\eta}\left(A_{k1}\left(\frac{\eta}{\eta+1}\right)\varphi\right)^{\eta}, \quad \pi(\varphi) = \frac{\eta^{\eta}}{(\eta+1)^{\eta+1}}\varphi^{\eta+1}A_{k1}^{\eta}W_r^{-\eta}.$$

For *constrained* firms we have

$$w(\varphi) = \underline{w}_c, \quad \ell(\varphi) = W_r^{-\eta}\left(A_{k1}\underline{w}_c\right)^{\eta}, \quad \pi(\varphi) = \left(\varphi - \underline{w}_c\right)\underline{w}_c^{\eta}A_{k1}^{\eta}W_r^{-\eta}.$$

F.1.4 Local labor markets: derivations

Recall that the cdf of productivity is $F_g(\varphi) = 1 - (\varphi/\varphi_{g0})^{\alpha}$ if $\varphi > \varphi_{g0}$ otherwise. The conditional cdf on some value x can be found by simply using x instead of φ_{g0} in the expression above. Also recall the value of the thresholds is $\overline{\varphi}_g = \underline{w}_c(\eta+1)/\eta$ and $\underline{\varphi}_g = \underline{w}_c$.

Share of firms bunching at the wage floor First, if $\varphi_{g0} > \overline{\varphi}_g > \underline{\varphi}_g$ all firms pay above the wage floor, thus $S_g = 0$. Second, if $\overline{\varphi}_g > \varphi_{g0} > \underline{\varphi}_g$, then the minimum productivity is φ_{g0}. The share of firms bunching at the wage floor is

$$\begin{aligned} S_g &= F_g\left(\overline{\varphi}(\underline{w}_{c(g)})\right) - F_g\left(\varphi_{g0}\right) = \left[\left(\frac{\varphi_{g0}}{\varphi_{g0}}\right)^{\alpha}\right] - \left[\left(\frac{\varphi_{g0}}{\overline{\varphi}(\underline{w}_{c(g)})}\right)^{\alpha}\right], \\ &= 1 - \left(\frac{\varphi_{g0}}{\underline{w}_{c(g)}}\right)^{\alpha}\left(\frac{\eta}{\eta+1}\right)^{\alpha}. \end{aligned} \tag{F.1}$$

Finally, if $\overline{\varphi}_g > \underline{\varphi}_g > \varphi_{g0}$, then the minimum productivity is $\underline{\varphi}_g = \underline{w}_c$. Thus,

$$\begin{aligned} S_g &= F_g\left(\overline{\varphi}(\underline{w}_{c(g)})\right) - F_g\left(\underline{\varphi}(\underline{w}_{c(g)})\right) = \left[\left(\frac{\underline{w}_c}{\underline{\varphi}(\underline{w}_{c(g)})}\right)^{\alpha}\right] - \left[\left(\frac{\underline{w}_c}{\overline{\varphi}(\underline{w}_{c(g)})}\right)^{\alpha}\right] \\ &= 1 - \left(\frac{\eta}{\eta+1}\right)^{\alpha}. \end{aligned}$$

This is the maximum share of observed firms bunching that is compatible with the model.

Average wage For any threshold x, the average wage of *unconstrained* firms is given by

$$\begin{aligned} \bar{w}_g^u &= \int_x^{\infty} w(z)f_g(z|x)dz \\ &= \int_x^{\infty}\left(\frac{\eta}{\eta+1}\right)z\alpha x^{\alpha}z^{-\alpha-1}dz \\ &= \left(\frac{\eta}{\eta+1}\right)\left(\frac{\alpha}{\alpha-1}\right)x \end{aligned}$$

Then, if $\varphi_{g0} \geq \overline{\varphi}_g$ there are no constrained firms, so that

$$\bar{w}_g^u = \left(\frac{\eta}{\eta+1}\right)\left(\frac{\alpha}{\alpha-1}\right)\varphi_{g0}.$$

Now, if $\overline{\varphi}_g > \varphi_{g0} > \underline{\varphi}_g$, the minimum productivity of unconstrained firms is $\overline{\varphi}_g$, implying

$$\bar{w}_g^u = \left(\frac{\alpha}{\alpha-1}\right)\underline{w}_c.$$

This holds whether $\varphi_{g0} > \underline{\varphi}_g$ or not.

The average wage of *constrained* firms is given by $\underline{w}_c$ if there are any constrained firms. If $\varphi_{g0} \geq \overline{\varphi}_g$ no firm is constrained so this quantity is not defined.

Then, the average wage in a local labor market is given by a weighted average of the unconstrained and constrained wages, where the weights are given by the share of firms bunching. Going over the computations for each case, we get

$$\bar{w}_g = \begin{cases} \left(\frac{\eta}{\eta+1}\right)\left(\frac{\alpha}{\alpha-1}\right)\varphi_{g0} & \text{if } \varphi_{g0} > \overline{\varphi}, \\ \left(1+\left(\frac{\varphi_{g0}}{\underline{w}_c}\right)^{\alpha}\left(\frac{1}{\alpha-1}\right)\left(\frac{\eta}{\eta+1}\right)^{\alpha}\right)\underline{w}_c & \text{if } \overline{\varphi} > \varphi_{g0} > \underline{\varphi}_g, \\ \left(1+\left(\frac{1}{\alpha-1}\right)\left(\frac{\eta}{\eta+1}\right)^{\alpha}\right)\underline{w}_c & \text{if } \overline{\varphi} > \underline{\varphi}_g > \varphi_{g0}. \end{cases} .$$

Aggregate quantities To compute aggregate labor demand in g we need to solve $L_g = M_g \int_{\varphi_{g0}}^{\infty} \ell(z) f_g(z) dz$. Solving the integral for each case we get:

$$L_g = M_g W_r^{-\eta} A_{k1}^{\eta} \begin{cases} \left(\frac{\eta}{\eta+1}\right)^{\eta}\left(\frac{\alpha}{\alpha-\eta}\right)\varphi_{g0}^{\eta} & \text{if } \varphi_{g0} > \overline{\varphi}_g, \\ \underline{w}_c^{\eta}\left\{1+\left(\frac{\eta}{\alpha-\eta}\right)\left(\frac{\eta}{\eta+1}\right)^{\alpha}\left(\frac{\varphi_{g0}}{\underline{w}_c}\right)^{\alpha}\right\} & \text{if } \overline{\varphi}_g > \varphi_{g0} > \underline{\varphi}_g, \\ \underline{w}_c^{\eta}\left(\frac{\varphi_{g0}}{\underline{w}_c}\right)^{\alpha}\left\{1+\left(\frac{\eta}{\alpha-\eta}\right)\left(\frac{\eta}{\eta+1}\right)^{\alpha}\right\} & \text{if } \overline{\varphi}_g > \underline{\varphi}_g > \varphi_{g0}, \end{cases}$$

and the partial derivative with respect to the wage floor, holding constant the wage index, is given by

$$\frac{\partial L_g}{\partial \underline{w}_c} = M_g W_r^{-\eta} A_{k1}^{\eta} \begin{cases} 0 & \text{if } \varphi_{g0} > \overline{\varphi}_g, \\ \underline{w}_c^{\eta-1}\eta\left\{1-\left(\frac{\eta}{\eta+1}\right)^{\alpha}\left(\frac{\varphi_{g0}}{\underline{w}_c}\right)^{\alpha}\right\} & \text{if } \overline{\varphi}_g > \varphi_{g0} > \underline{\varphi}_g, \\ \underline{w}_c^{\eta-1}\left(\frac{\varphi_{g0}}{\underline{w}_c}\right)^{\alpha}(\eta-\alpha)\left\{1+\left(\frac{\eta}{\alpha-\eta}\right)\left(\frac{\eta}{\eta+1}\right)^{\alpha}\right\} & \text{if } \overline{\varphi}_g > \underline{\varphi}_g > \varphi_{g0}. \end{cases}$$

These equations imply that the effect of the wage floor on employment is hump-shaped, a result first derived by Ahlfeldt et al. (2022) in a more general model where there are also firms that can ration employment.

To compute the aggregate wage bill in g we need to solve $WB_g = M_g \int_{z^{\min}}^{\infty} w(z)\ell(z) f_g(z) dz$.

The result is given by

$$WB_g = M_g W_r^{-\eta} A_{k1}^{\eta} \begin{cases} \varphi_{g0}^{\eta+1} \left(\frac{\eta}{\eta+1}\right)^{\eta+1} \left(\frac{\alpha}{\alpha-\eta-1}\right) & \text{if } \varphi_{g0} \geq \overline{\varphi}_g, \\ \underline{w}_c^{\eta+1} \left\{1 + \left(\frac{\eta+1}{\alpha-\eta-1}\right) \left(\frac{\eta}{\eta+1}\right)^{\alpha} \left(\frac{\varphi_{g0}}{\underline{w}_c}\right)^{\alpha}\right\} & \text{if } \overline{\varphi}_g > \varphi_{g0} \geq \underline{\varphi}_g, \\ \underline{w}_c^{\eta+1} \left(\frac{\varphi_{g0}}{\underline{w}_c}\right)^{\alpha} \left\{1 + \left(\frac{\eta+1}{\alpha-\eta-1}\right) \left(\frac{\eta}{\eta+1}\right)^{\alpha}\right\} & \text{if } \varphi_{g0} < \underline{\varphi}_g, \end{cases}$$

and the derivative of WB_g with respect to the wage floor, holding constant the wage index, is

$$\frac{\partial WB_g}{\partial \underline{w}_c} = M_g W_r^{-\eta} A_{k1}^{\eta} \begin{cases} 0 & \text{if } \varphi_{g0} \geq \overline{\varphi}_g, \\ \underline{w}_c^{\eta}(\eta+1) \left[1 - \left(\frac{\eta}{\eta+1}\right)^{\alpha} \left(\frac{\varphi_{g0}}{\underline{w}_c}\right)^{\alpha}\right] & \text{if } \overline{\varphi}_g > \varphi_{g0} \geq \underline{\varphi}_g, \\ \underline{w}_c^{\eta} \left(\frac{\varphi_{g0}}{\underline{w}_c}\right)^{\alpha} \alpha \left[\frac{\eta+1}{\alpha}\left(1 - \left(\frac{\eta}{\eta+1}\right)^{\alpha}\right) - 1\right] & \text{if } \overline{\varphi}_g > \underline{\varphi}_g > \varphi_{g0}. \end{cases}$$

Finally, aggregate revenue can be obtained from $R_g = M_g \int_{z^{\min}}^{\infty} z\ell(z) f_g(z) dz$. The solution is given by

$$R_g = M_g W_r^{-\eta} A_{k1}^{\eta} \begin{cases} \varphi_{g0}^{\eta+1} \left(\frac{\eta}{\eta+1}\right)^{\eta} \left(\frac{\alpha}{\alpha-\eta-1}\right) & \text{if } \varphi_{g0} \geq \overline{\varphi}_g, \\ \underline{w}_c^{\eta} \varphi_{g0} \left(\frac{\alpha}{\alpha-1}\right) \left\{1 + \left(\frac{\eta}{\alpha-\eta-1}\right) \left(\frac{\eta}{\eta+1}\right)^{\alpha-1} \left(\frac{\varphi_{g0}}{\underline{w}_c}\right)^{\alpha-1}\right\} & \text{if } \overline{\varphi}_g > \varphi_{g0} \geq \underline{\varphi}_g, \\ \underline{w}_c^{\eta+1} \left(\frac{\varphi_{g0}}{\underline{w}_c}\right)^{\alpha} \left(\frac{\alpha}{\alpha-1}\right) \left\{1 + \left(\frac{\eta}{\alpha-\eta-1}\right) \left(\frac{\eta}{\eta+1}\right)^{\alpha-1}\right\} & \text{if } \overline{\varphi}_g > \underline{\varphi}_g > \varphi_{g0}. \end{cases} \tag{F.2}$$

Once again, the partial derivative with respect to the wage floor is

$$\frac{\partial R_g}{\partial \underline{w}_c} = M_g W_r^{-\eta} A_{k1}^{\eta} \begin{cases} 0 & \text{if } \varphi_{g0} \geq \overline{\varphi}_g, \\ \underline{w}_c^{\eta-1} \varphi_{g0} \eta \left(\frac{\alpha}{\alpha-1}\right) \left[1 - \left(\frac{\eta}{\eta+1}\right)^{\alpha-1} \left(\frac{\varphi_{g0}}{\underline{w}_c}\right)^{\alpha-1}\right] & \text{if } \overline{\varphi}_g > \varphi_{g0} \geq \underline{\varphi}_g, \\ \underline{w}_c^{\eta} \left(\frac{\varphi_{g0}}{\underline{w}_c}\right)^{\alpha} \alpha \left[\frac{\eta}{\alpha-1}\left(1 - \left(\frac{\eta}{\eta+1}\right)^{\alpha-1}\right) - 1\right] & \text{if } \overline{\varphi}_g > \underline{\varphi}_g > \varphi_{g0}. \end{cases} \tag{F.3}$$

To solve the Nash bargaining problem, it is useful to compute the total derivative with respect to the wage floor. Let $X \in \{L, WB, R\}$ be any of the aggregate quantities defined above. Then, the total derivative is given by

$$\frac{dX_g}{d\underline{w}_c} = \frac{\partial X_g}{\partial \underline{w}_c} - \eta \frac{X_g}{W_r} \frac{dW_r}{d\underline{w}_c},$$

where $dW_r/d\underline{w}_c$ is the derivative of the wage index with respect to the wage floor.

F.2 Equilibrium of structural model

F.2.1 Definition of equilibrium

Given a CBA network $\mathcal{C}$, values for $\{\{N_r\}_{r\in\mathcal{R}}, \{M_g\}_{g\in\mathcal{G}}\}$, parameters for the worker problem $\{\zeta, \{b_r\}_{r\in\mathcal{R}}, \eta, \{A_{k1}\}_{k1\in\mathcal{K}1}\}$, bargaining power parameters $\{\beta_c\}_{c\in\mathcal{C}}$, and productivity processes parameters $\{\alpha, \{\varphi_{g0}\}_{g\in\mathcal{G}}\}$, an equilibrium is defined as a vector of employment shares $\{\mu_r\}_{r\in\mathcal{R}}$, a set of wage floors $\{w_c^*\}_{c\in\mathcal{C}}$, and a set of wage indices $\{W_r^*\}_{r\in\mathcal{R}}$ such that:

1. Employment shares satisfy equation (8), with expected utility given by (7).

2. Firms at every z choose wages given labor supply according to (9).

3. Wage floors simultaneously solve the Nash-in-Nash problem given by (13) for all $c \in \mathcal{C}$.

4. Wage indices clear the labor market in each region:

$$\sum_{g:r(g)=r} M_g \int_{\varphi_{g0}}^{\infty} \ell(z) f_g(z) dz = \mu_r N_r. \tag{F.4}$$

Existence and uniqueness of equilibrium. Let $\hat{\Gamma} = \Gamma(\frac{\eta-1}{\eta})^{\zeta}$ and write $\hat{L}_r = \sum_{g:r(g)=r} \hat{L}_g$. Then, the market clearing condition can be written as

$$W_r^{-\eta} \hat{L}_r = \frac{\hat{\Gamma} W_r^{\zeta}}{\hat{\Gamma} W_r^{\zeta} + b_r} N_r. \tag{F.5}$$

This is a continuous function of W_r, and applying the intermediate value theorem we can conclude that a unique solution exists for any vector of wage floors.[14]

Then, it remains to discuss the equilibrium of the Nash-in-Nash problem. If all objective functions were concave, then the problem would be a concave maximization problem over a convex set, and thus a unique solution would exist. However, the objective functions may actually be decreasing at first, increasing later on, and then decreasing again. These "convex regions" would happen if an increase in the wage floor decreases the wage bill, either due to general equilibrium effects or because some low productivity local labor markets are fully constrained by the wage floor and experience negative wage floor effects. However, an objective function with a concave region is not a problem if a global maximum to it exists. There will not be a unique maximum in case a local maximum following a decline in the objective function generates a value of the objective function equal to the value when the wage floor is non-binding.

In summary, the Nash-in-Nash problem has a unique solution if all objective functions in the Nash-in-Nash problem are concave. If there are convex regions, then a unique solution exists if the global maximum of a given problem is unique.

Effect of wage floor on regional wage index. A closed form solution to (F.5) does not exist. However, we can obtain an expression for the derivative of the wage index with respect to the

[14]Define $h(W_r) = W_r^{-\eta} \hat{L}_r = \frac{\hat{\Gamma} W_r^{\zeta}}{\hat{\Gamma} W_r^{\zeta} + b_r} N_r$. Then, $W_r \to 0$ implies that $h(0) \to \infty$ and $W_r \to \infty$ implies that $h(\infty) \to -N_r$. Thus, by the intermediate value theorem, there exists a W_r^* such that $h(W_r^*) = 0$.

wage floor using the implicit function theorem:

$$\frac{dW_r}{d\underline{w}_c} = \frac{\left(\hat{\Gamma} W_r^{\zeta} + b_r\right)}{\hat{\Gamma} W_r^{\zeta-1}\left[(\zeta+\eta)W_r^{\eta} N_r - \zeta \hat{L}_r\right]} \sum_{g:c(g)=c} \frac{\partial \hat{L}_g}{\partial \underline{w}_c}. \tag{F.6}$$

F.2.2 An algorithm to compute the equilibrium

Given a set of parameters, I solve for equilibrium wage indices $\{W_r\}_{r\in\mathcal{R}}$ and wage floors $\{w_c\}_{c\in\mathcal{C}}$ using an algorithm that mixes fixed-point iteration and Gauss-Seidel's coordinate update algorithm (See Galichon 2022). The algorithm proceeds as follows:

1. Take an initial guess $\{\{W_r^0\}, \{\underline{w}_c^0\}\}$
2. Use fixed-point iteration to find equilibrium wage indices $\{W_r^1\}$ using the latest value for wage floors.
3. Iteratively find equilibrium wage floors $\{\underline{w}_c^1\}$ numerically solving the the Nash bargaining split for each c, using the equilibrium wage indices $\{W_r^1\}$ and the previously found wage floors.
4. Take $\{\{W_r^1\}, \{\underline{w}_c^1\}\}$ as new starting point and repeat.
5. Iterate until convergence.

I set as starting point $W_r = .5$ for every r, and $\underline{w}_c = 1.05 \times \min_{c:g(c)=c}\{z_{g0}\}$ for every c. Setting as criteria that the mean absolute difference between consecutive iterations is less than 10^{-8}, I have found the algorithm to converge in 3 to 6 iterations. I set the same criterion for the inner fixed-point iteration to find regional wage indices.

Finding wage indices. Using the four labor market-clearing equations it is straightforward to write $W_r = T(W_r)$, where $T(\cdot)$ is a contraction mapping. In particulae, using (F.5), we can write

$$W_r = \left(\frac{\hat{\Gamma} W_r^{\zeta} + b_r}{\hat{\Gamma} W_r^{\zeta}} \frac{\hat{L}_r}{N_r}\right)^{1/\eta}.$$

Thus, to find wage indices I use a fixed-point iteration using the most up-to-date wage floors to compute aggregate labor demand.

Finding wage floors. In this step I use the Nash bargaining FOCs, first defined in equation (2). However, it turns out that this presents some complications with the local labor markets data. To deal with them, I select several candidate points for maximizers and then evaluate the bargaining objective function to select the global maximum.

The first issue is that the derivatives of the wage bill and revenue are discontinuous when $z_{g0} = \underline{w}_c$, i.e., when g is fully constrained by $\underline{w}_c$. Fortunately, this happens only in a small share sectors, usually belonging to the largest CBAs. As a result, derivatives are generally well-defined in the feasible range where the wage floor will be set. However, for different counterfactuals this might not be the case. As a result, I add all points where $z_{g0} = \underline{w}_c$ for some g as candidate points for maximizers.

Secondly, when there are multiple local labor markets in a CBA, the objective functions are sums of terms, some of which do not depend on the wage floor (the unconstrained ones). Similarly, the set of local labor markets that enter the derivatives will depend on what labor markets are constrained by the wa floor. This generates the possibility of local optima, where equation (2) is satisfied, but the objective function may not be maximized. To deal with this, I search for all wage floors at which equation (2) holds and add them to the set of candidate maximizers.

Finally, I evaluate all candidate points and pick the one that yields the global maximum.

F.3 Defining local labor markets and summarizing data

The coarsening of 4-digit sectors attempts to prevent detailed sectors with too few workers. The grouping of provinces is as follows: (1) "Centro" includes Ciudad de Buenos Aires, Buenos Aires, Córdoba, Entre Ríos, La Pampa, Mendoza, and Santa Fe; (2) "Cuyo" includes La Rioja, Mendoza, San Juan, and San Luis; (3) "Norte" includes Catamarca, Chaco, Corrientes, Formosa, Jujuy, Misiones, Salta, and Tucumán; and (4) "Patagonia" includes Chubut, La Pampa, Neuquén, Río Negro, Santa Cruz, and Tierra del Fuego.

I divide sector by region cells using the observed CB network $\mathcal{C}$, relying on the "primary CBA" of firms defined in Appendix B.4. I take this approach to avoid dropping workers or misclassifying workers in a CBA they don't belong to. If a CBA has a number of firms above a threshold in a sector-region cell, or if it represents a minimum percent of all firms in the CBA, I consider it its own local labor market. Firms in CBAs that do not meet these criteria are grouped in a separate local labor market under a "local CBA" category.[15] Finally, if a local CBA has less than 20 workers or less than 2.5% of workers have a wage floor assigned to them, I impute the modal CBA in the region-sector cell.

I estimate wage floors by taking the mean of the firm-level average wage floor in each CBA. I allow regional wage floors within a CBA only if the region's average wage floor is sufficiently different from the rest.[16] Specifically, I classify wage floors into different categories based on their percentage difference from the mean. If the maximum difference is less than 5%, I define the wage floor as the average. If the difference is greater and the maximum is in Patagonia, I assign the maximum to Patagonia and average the rest. I extend a similar logic to CBAs with more than one regional wage floor, and implement a handful of manual adjustments. I consider regional differences in wage floors as constant when estimating the effects of shocks, and allow a single wage floor per CBA to be determined in the negotiations. This aligns with usual practice in

[15] Furthermore, I create a separate sector within each 1-digit sector to group a small percentage of firms that end up in a local labor market with less than 25 workers, or less than 2.5 of workers with an assigned wage floor.

[16] For example, the retail CBA 0130/75 has a higher wage floor for the region of Patagonia.

CBAs, where regional differences are usually constant. Appendix Figure 17 shows the estimates.

There are some concerns of measurement error in wage floors, which complicate the computation of the share of firms bunching at the wage floor. First, wage floors are estimated from data, which means they are noisy. Small CBAs and categories within CBAs with a few workers are both lost in this step. Second, workers earning less than the wage floor are common. I define a worker to be part-time if she earns less than 90% of the wage floor. I define a worker to be a "buncher" (that is, a worker with a deviation of 0 from the wage floor) if she is full-time and her wage is between 90 and 105% of the floor, or if she is part-time and her wage is between 40 and 60% of the floor. There are many workers who earn less than 40% of the wage floor.[17] I drop firms with a large share of these workers to compute local labor market quantities. Finally, there are many workers for which I don't observe both the CBA code and the occupation category.

I compute the share of firms constrained by taking the share of firms with an average deviation of the wage floor of zero. When a local labor market has a large share of workers with an unobserved wage floor, I impute the share of firms that are bunching using a regression model. I further shrink the estimated share of firms bunching using the James-Stein estimator towards the region by 3-digit sector average.

I also compute the mean of firm-level average wages in each local labor market. To do so I adjust for the share of part-time workers by doubling their wage when computing their average.

F.4 Estimating model parameters

Preference heterogeneity parameter η. To estimate η, I exploit the relationship between firm size ℓ and wages w implied by (6). To do so, I regress log wages on log employment at the firm level controlling for region and 1-digit sector fixed effects. However, the structure of labor supply implies an exact fit of this regression.

To allow for a non-perfect fit the model can be extended to incorporate hours. In particular, assume that production takes place before the firm draws a random value h such that realized employment is $\ell^* = h\ell$. In that case, the labor supply to the firm equation can be written as $\ell^*(j) = hW_r^{-\eta}A_{k1}^{\eta}w(j)^{\eta}$, and so by taking logs and rearranging terms I can write observed log wages as a function of observed log employment and $\ln h$ plays the role of the error term.

Specifically, I use the firm-level data and estimate the regression

$$\ln w_{jt} = \bar{\eta}\ln \ell_{jt} + b_{k1(j)} + \delta_{r(j)t} + \nu_{jt}.$$

where $k1(j)$ is the 1-digit sector of firm j and $\delta_{r(j)t}$ corresponds to year by region fixed effects. Under the assumption that unobservables (hours) are uncorrelated with firm size within regions and time periods, the coefficient $\bar{\eta}$ identifies the inverse of η.

Appendix Table 12 shows the estimates, which are stable when varying the set of fixed effects included in the regression. My preferred specification is column (3), which yields $\eta = 4.0995 \approx$

[17] The average firm-level share of workers that earn less than 40% of the wage floor is approximately 0.13.

1/0.2439. The literature provides other values for this parameter. Monte et al. (2018) in the US use county-level data and estimate a value of 3.3. Ahlfeldt et al. (2022) for Germany use a firm-level dataset and find a value of 5.2. Parente (2022) uses a calibration approach in Brazil and finds values of 4.52 and 4.22 for 1996 and 2012, respectively. Datta (2023) estimates a labor supply elasticity of 4.6 in the UK using HR data from a multi-establishment firm.

I also rely on column (3) of Appendix Table 12 to obtain my estimates of the amenity values $\{A_{k1}\}_{k1\in\mathcal{K}1}$. The omitted category is chosen so that all b_{k1} are positive. Then, using the model structure I compute $A_{k1} = \exp(-b_{k1})$, which results in values ranging from 1 to 1.81. The amenity values allow firms to have different sizes conditional on the wage across 1-digit sectors.

Preference for formal employment ζ. From equation (8) the extensive-margin labor supply elasticity can be computed to be

$$\frac{d\mu_r}{dV_r}\frac{V_r}{\mu_r} = \zeta(1-\mu_r).$$

The elasticity is estimated to be around 0.2 in the literature (Chetty et al. 2011). Using the average share of formal employment from Appendix Table 13, I set $\zeta = 0.2813$. Differences in the shares of formal employment across regions will load on outside options.

Shape of productivity distributions α. As discussed in Section 6.2.2, the maximum share of firms constrained by the wage floor that is consistent with the model is given by

$$S_g^{\max} = 1 - \left(\frac{\eta}{\eta+1}\right)^{\alpha}.$$

I invert this expression for α and plug-in the 99.5th percentile of the share of firms constrained by the wage floor for $S_g^{\max}$ and the value of η estimated above. I use the 2014-2015 data as shares constrained are somewhat higher in this period. I obtain $\alpha = 5.6227$. For comparison, Parente (2022) uses a Pareto-LogNormal distribution where the shape of the Pareto is calibrated to 6.02 and 6.33 in two different periods.

Minimum productivities. I invert the share of firms constrained by the wage floor to obtain the minimum productivities $\{\varphi_{z_{g0}}\}_{g\in\mathcal{G}}$. First, if the share of firms constrained by the wage floor is zero, then I set $\varphi_{z_{g0}} = (\eta/(\eta+1))\underline{w}_c$. This assumes that the productivity is the minimum value that allows the local labor market to be unconstrained. Second, if the share of firms constrained is equal to the maximum possible share, then I set $\varphi_{z_{g0}} = \underline{w}_c$. This assumes that the productivity is the minimum value that makes the local labor market to be fully constrained. These two cases are rare, and happen only in a few small local labor markets. Finally, for all other observed values $S_g = s$ I invert equation (F.1), which results in

$$\varphi_{z_{g0}} = \underline{w}_c\,(1-s)^{1/\alpha}\left(\frac{\eta}{\eta+1}\right).$$

For a given $\underline{w}_c$, a larger observed share s implies that productivity must be lower.

Outside options b_r. To obtain outside options I use equation (8), which requires computing V_r. Furthermore, V_r requires knowledge of regional wage indexes W_r. So, I proceed as follows. First, noting that $L_g = W_r^{\eta}\hat{L}_g$, I compute wage indexes using the labor market clearing condition:

$$W_r = \left(\frac{\sum_g \hat{L}_g}{\mu_r N_r}\right)^{1/\eta},$$

where μ_r and N_r are obtained from household survey data. In particular, N_r is the number of private sector workers (formal or informal), and μ_r the share of formal private sector workers.[18] Then, equation (7) is used to obtain V_r. Finally, I compute b_r inverting equation (8). Appendix table 13 shows the results.

Bargaining power parameters. I invert the closed form expression for the Nash bargaining solution of each CBA to obtain the bargaining power parameters, which is given by (2). This condition will hold in any equilibrium with $\underline{w}_c < \min_{g:c(g)=c}\{\varphi_g\}$, i.e., when no market is maximally constrained by the wage floor.[19] It turns out that nearly all local labor markets satisfy this condition, with only 6 found where the maximum share of firms bunching is observed. Importantly, the inversion relies on computing the equilibrium value of the derivative of the objective functions of the union and the employer association with respect to the wage floor, both of which enter the bargaining weight.

Let $\gamma_c = WB_c/R_c$ be the share of the wage bill of the union in local labor market, computed using equilibrium quantities. Then, the bargaining power parameters are computed as

$$\beta_c = \frac{\gamma_c}{\gamma_c + (1-\gamma_c)\left(-\frac{dU}{d\underline{w}_c}\Big/\frac{d\Pi}{d\underline{w}_c}\right)}.$$

Note that these derivatives are evaluated at the equilibrium wage floors and wage indexes, and include the general equilibrium term $dW_r/d\underline{w}_c$ from equation (F.6). Since γ_c is bound by construction in the model, the key variation used to obtain the bargaining parameters comes from the ratio of the derivatives of U and Π with respect to the wage floor. The distribution of the ratio of derivatives is shown in Panel (a) of Appendix Figure 20. Panel (b) of Appendix Figure 20 shows the estimated bargaining power parameters.

[18]Formal workers are those that declare to contribute to the social pension system.

[19]If this condition does not hold the optimal wage floor may be found in a point where the derivatives do not exist. For instance, the wage bill function of a single local labor market is maximized when the wage floor equals the minimum productivity.

G Additional Tables and Figures

Appendix Table 1: Description of areas of representation for selected collective bargaining agreements (CBAs) in the textile industry

CBA	Spanish	English
0500/07	Obreros de la industria textil, son los ocupados en establecimientos cuya actividad principal comprenda procesos destinados a la confección de colchones, bolsas, tejer, lavar, clasificar, peinar, cardar, hilar, urdir, tramar, retrocer, estrusar, devanar, desfibrar, teñir, aprestar, texturizar, bordar, cortar, coser, atar, anudar, bobinar, planchar, estampar, terminar, o similares y que se lleve a cabo sobre cualquier tipo de fibras, sean naturales o manufacturadas, ya sea manualmente o mediante la utilización de maquinarias subordinadas al proceso industrial textil.	Workers in the textile industry are those engaged in establishments whose main activity involves processes intended for making mattresses, bags, knitting, washing, sorting, combing, carding, spinning, warping, weaving, twisting, extruding, winding, defibring, dyeing, finishing, texturing, embroidering, cutting, sewing, tying, knotting, spooling, ironing, stamping, completing, or similar activities, carried out on any type of fibers, whether natural or manufactured, either manually or through the use of machinery subordinate to the textile industrial process.
0501/07	Trabajadores, empleados, supervisores, encargados, mecánicos, personal auxiliar de ambos sexos, de administración, de comercialización y de fábrica únicamente de las empresas industriales de indumentaria y afines.	Workers, employees, supervisors, managers, mechanics, auxiliary staff of both genders, from administration, sales, and exclusively from clothing industrial companies and related fields.
0746/17	Todos los trabajadores de la industria de la confección de indumentaria y afines según se especifican en los respectivos capítulos de la misma, comprende también a las empresas que fabrican toldos en general y sus respectivos accesorios, en artículos con tela de lona, plástica, sintéticas y/o similares, empresas que confeccionan y arman colchones en general y con sus respectivos accesorios, con todo tipo de materiales. Están comprendidos también los lavaderos industriales de los procesos de producción, tanto internos como externos. También incluye las empresas que producen avíos y accesorios internos para todo tipo de prendas de vestir en general, cualquiera fuere el material empleado en su producción y/o elaboración.	All workers in the apparel manufacturing industry and related fields as specified in the respective [CBA] chapters. This also includes companies that manufacture awnings in general and their respective accessories, in articles made of canvas fabric, plastic, synthetic and/or similar materials. It also covers companies that make and assemble mattresses in general and their accessories, with all types of materials. Also included are industrial laundries involved in the production process, both internal and external. It also includes companies that produce fittings and internal accessories for all types of clothing in general, regardless of the material used in their production and/or manufacturing.

Notes: The figure shows the description of the areas of representation for three selected collective bargaining agreements in the textile industry. The three CBAs specify the entire country as their regional scope. The description in Spanish is verbatim from the CBA, and the description in English is a translation obtained using the large language model GPT-4.

Appendix Table 2: Mandatory usage of Employee Registry by number of workers

Period	**Threshold (num. of workers)**
January 2008 to July 2012	10
August 2012 to March 2013	25
April 2013 to March 2014	100
April 2014 to March 2015	200
April 2015 to April 2016	300
May 2016 to July 2017	400
August 2017 to November 2017	600
December 2018 to July 2018	2000
August 2018 onwards	Any

Source: Resolución general AFIP 4265/2018.

Appendix Table 3: Summary statistics of main estimating sample, firm cross-section

	N	Mean	Std. Dev	Min	Max
Unique 4d sector	221				
Unique 6d sector	462				
Firm shock (2013-12 vs. 2010-09)	7,604	0.4737	0.3642	-1.3186	4.2672
Pre firm shock (2010-09 vs. 2008-07)	7,604	0.2856	0.4217	-1.9982	4.2070
Average employment 2007-09	7,604	46.18	55.66	1.00	396.33
Indicator employment 2007-09 $\leq$10	7,604	0.2336	0.4231	0.0000	1.0000
Average monthly wage 2007-09 (2010 ARS)	7,604	3,605.21	2,527.41	428.75	57,295.78
Log mean value exported 2011-2012	7,604	11.2523	2.1841	6.0638	16.9391
Observed in survey data	7,604	0.2257	0.4181	0.0000	1.0000

Notes: Data are from the baseline sample of firms that exported in 2011–2012. The tables show summary statistics of the data used in the main difference-in-differences estimates.

Appendix Table 4: Summary statistics of main estimating sample, CB units cross-section

	N	Mean	Std. Dev	Min	Max
Shock 2013-2012 minus 2010-09	152	0.5440	0.6967	-1.3186	4.2672
Shock 2010-2009 minus 2007-08	152	0.3829	0.8357	-1.9982	4.2070
Num. firms 2011-12	152	3,408.27	22,103.75	30	263,629
Num. firms in baseline sample 2011-12	152	50.03	253.30	1	2,219
Share employment exporting firms 2011-12	152	0.3324	0.2668	0.0103	0.9138

Notes: Data are from a panel of firms that exported in 2011–2012. The tables show summary statistics of the data used in the main difference-in-differences estimates.

Appendix Table 5: Summary statistics of main estimating sample, firm panel

	N	Mean	Std. Dev	Min	Max
Year	82,265	2,011.94	3.15	2,007	2,017
CB shock 2013-2012 minus 2010-09	82,265	0.4738	0.3652	-1.3186	4.2672
Firm shock 2013-2012 minus 2010-09	82,265	0.4312	0.3493	-3.6234	3.2670
Log average monthly wage	48,633	7.8385	0.1942	6.6289	9.6323
Log average monthly wage floor	81,821	3.2326	1.1974	0.0000	8.5142
Log employment	81,617	3.1487	1.1879	0.0000	8.4933
Share main hiring modality	82,265	0.6872	0.2837	0.0000	1.0000
Indicator active firm	83,644	0.9835	0.1273	0.0000	1.0000

Notes: Data are from a panel of firms that exported in 2011–2012. The tables show summary statistics of the data used in the main difference-in-differences estimates.

Appendix Table 6: Static difference-in-differences estimates, heterogeneity by pre-period mean wage

	Log mean wage	Log mean wage floor	Log wage cushion	Log employment	Sh. main modality
	(1)	(2)	(3)	(4)	(5)
CB shock × Pre wage 1	0.1056	0.1083	0.0506	-0.1989	-0.0951
	(0.0625)	(0.0183)	(0.0475)	(0.0799)	(0.0332)
CB shock × Pre wage 2	0.1375	0.1060	-0.0200	0.0440	0.0361
	(0.0487)	(0.0336)	(0.0350)	(0.0769)	(0.0332)
CB shock × Pre wage 3	0.1157	0.1134	-0.0306	0.1944	0.0541
	(0.0281)	(0.0276)	(0.0472)	(0.0832)	(0.0323)
CB shock × Pre wage 4	0.0543	0.1137	-0.0321	-0.0979	0.0261
	(0.0552)	(0.0322)	(0.0566)	(0.1102)	(0.0512)
p-value CB shock 1-2	0.5671	0.9324	0.2706	0.0426	0.0026
p-value CB shock 1-3	0.8811	0.7874	0.2171	0.0002	0.0000
p-value CB shock 1-4	0.6041	0.8573	0.3392	0.3898	0.0099
Firm shock	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes
Wage level-local market-year FE	Yes	Yes	Yes	Yes	Yes
Pre-period CB shock	Yes	Yes	Yes	Yes	Yes
Num. firms	6,714	6,526	6,526	6,714	6,714
Num. fixed effects	25,493	18,095	18,095	25,493	25,551
Num. observations	72,287	43,423	43,419	72,287	72,660
Adjusted R^2	0.8565	0.9223	0.8353	0.8987	0.6402

Notes: Data are from the baseline panels of firms, excluding CB unit by province cells with less than 8 firms. The sample is analogous to the one in Table 1. The figure shows regression coefficients on the CB shocks interacted with an indicator for year greater than or equal to 2012. The CB shock variable is further interacted with an indicator for whether the average firm wage in 2007–2009 is in the first ("Pre wage 1"), second ("Pre wage 2"), third ("Pre wage 3") or fourth ("Pre wage 4") quartile of the distribution of firm wages in the province by CB unit cell in 2007–2009. The p-values are for the null hypothesis that the coefficient on the CB shock interacted with Pre wage 1 is equal to the coefficient on the CB shock interacted with Pre wage 2, Pre wage 3, or Pre wage 4. The regression models in terms of included controls are analogous to the ones in Table 1, including controls for the firm shock. Standard errors, included for the hypothesis testing, are clustered at the CB level.

Appendix Table 7: Static difference-in-differences estimates, robustness to sector controls

	Log mean wage			Log employment			Log mean wage floor		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CB shock	0.0482	0.0343	0.0450	-0.0197	-0.0190	0.0163	0.0505	0.0542	0.0413
	(0.0183)	(0.0236)	(0.0129)	(0.0353)	(0.0370)	(0.0238)	(0.0197)	(0.0223)	(0.0150)
Firm shock	0.0173	0.0142	0.0224	0.0388	0.0290	0.0461	-0.0026	-0.0035	-0.0021
	(0.0093)	(0.0091)	(0.0088)	(0.0194)	(0.0205)	(0.0183)	(0.0024)	(0.0026)	(0.0023)
6d sector shock			0.0050			-0.0267			-0.0025
			(0.0042)			(0.0116)			(0.0021)
Set of workers	All	All	All	All	All	All	All	All	All
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2d sector by province by year FE	No	No	Yes	No	No	Yes	No	No	Yes
4d sector by province by year FE	Yes	No	No	Yes	No	No	Yes	No	No
6d sector by province by year FE	No	Yes	No	No	Yes	No	No	Yes	No
Num. firms	7,601	7,601	7,583	7,601	7,601	7,583	7,331	7,331	7,314
Num. fixed effects	19,608	25,126	13,195	19,608	25,126	13,195	14,605	17,913	10,700
Num. observations	81,789	81,789	81,652	81,789	81,789	81,652	48,613	48,613	48,556
Adjusted R^2	0.8503	0.8528	0.8496	0.8991	0.9022	0.8989	0.9275	0.9308	0.9249

Notes: Data are from the baseline sample of exporting firms. The figure show regression coefficients on the firm, CB, and 6-digit sector shocks variables interacted with an indicator for year greater than or equal to 2012. The regression models are analogous to the ones in Table 1, but changing the approach to control for local labor market effects. The economic sector categories are constructed from a 6-digit economic sector variable that is similar to the revision 4 ISIC codes. Standard errors are clustered at the CB level for the CB shock variable, at the firm level for the firm shock variable, and at the 6-d sector level for the 6d sector shock variable.

Appendix Table 8: Static difference-in-differences estimates, worker level

	Log mean wage				
	(1)	(2)	(3)	(4)	(5)
CB shock	0.0206	0.0134	0.0261		0.0224
	(0.0061)	(0.0093)	(0.0114)		(0.0051)
CB shock × Main CB				0.0290	
				(0.0123)	
CB shock × Secondary CB				0.0077	
				(0.0144)	
Firm shock	Yes	Yes	Yes	Yes	No
Worker-firm FE	Yes	Yes	Yes	Yes	No
Firm-year FE	No	No	No	No	Yes
Worker FE	No	No	No	No	Yes
2d sector-province-year FE	Yes	No	No	No	No
4d sector-province-year FE	No	Yes	No	No	No
6d sector-province-year FE	No	No	Yes	Yes	No
2d sector-secondary CB-year FE	Yes	Yes	Yes	Yes	No
Hiring modality-year FE	Yes	Yes	Yes	Yes	No
Num. fixed effects	122,901	127,149	130,822	130,822	184,440
Num. observations	782,131	782,131	782,131	782,131	837,863
Adjusted R^2	0.8727	0.8792	0.8846	0.8846	0.9101

Notes: Data are a panel of workers that worked in exporting firms in 2011–2012 in all years 2008 through 2014. The table shows estimates of the effect of CB shocks on mean monthly wage. Columns (1) to (3) show estimates a difference-in-differences model using the main CB shock variable in the firm as treatment. Column (4) replicates column (3), but interacts the primary CB shock with an indicator for whether the worker's CB unit is the primary CB unit in the firm. Column (5) shows estimates of a difference-in-differences model using the CB unit of the worker to define the treatment. The "2d sector-secondary CB-year FE" include interactions between 2-digit sector, an indicator for whether the worker's CB is the primary CB in the firm, and year indicators. The "Hiring modality-year FE" include interactions between all possible hiring modality indicators as of 2008 with year indicators. Standard errors are clustered at the CB level for the CB shocks, and at the firm level for the firm shocks.

Appendix Table 9: Static difference-in-differences estimates, robustness to specification

	Log mean wage				Log employment			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CB shock	0.0482	0.0490	0.0481	0.0470	-0.0197	-0.0184	-0.0204	-0.0196
	(0.0183)	(0.0179)	(0.0182)	(0.0211)	(0.0353)	(0.0338)	(0.0355)	(0.0350)
Firm shock	0.0173	0.0211	0.0172	0.0168	0.0388	0.0304	0.0385	0.0388
	(0.0093)	(0.0092)	(0.0093)	(0.0093)	(0.0194)	(0.0194)	(0.0194)	(0.0194)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	No	Yes	Yes	Yes	No	Yes	Yes
Pre-period firm shock	No	No	Yes	No	No	No	Yes	No
Pre-period CB shock	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Local labor market by year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Num. firms	7,601	7,604	7,601	7,601	7,601	7,604	7,601	7,601
Num. fixed effects	19,608	17,812	19,608	19,608	19,608	17,812	19,608	19,608
Num. observations	81,789	81,821	81,789	81,789	81,789	81,821	81,789	81,789
Adjusted R^2	0.8503	0.8505	0.8503	0.8501	0.8991	0.8981	0.8992	0.8991

Notes: Data are from the baseline sample of exporting firms. The table show regression coefficients on the firm and CB shocks variables interacted with an indicator for year greater than or equal to 2012, varying the set of included controls. All outcomes are computed using the full set of workers in the firm-year. The regression models are analogous to the ones in Table 1, but changing the set of included controls. Standard errors are clustered at the CB level for the CB shock variable, and at the firm level for the firm shock variable.

Appendix Table 10: Static difference-in-differences estimates, robustness to inclusion of CB units

	Log mean wage				Log employment			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CB shock	0.0482	0.0320	0.0616	0.0330	-0.0197	-0.0066	-0.0474	-0.0400
	(0.0183)	(0.0168)	(0.0189)	(0.0187)	(0.0353)	(0.0291)	(0.0369)	(0.0407)
Firm shock	0.0173	0.0156	0.0153	0.0285	0.0388	0.0359	0.0351	0.0145
	(0.0093)	(0.0090)	(0.0094)	(0.0109)	(0.0194)	(0.0192)	(0.0195)	(0.0227)
Excluded CB units (num. firms)	< 30	None	< 100	< 30	< 30	None	< 100	< 30
Include 0130/75 (retail CB unit)	Yes	Yes	Yes	No	Yes	Yes	Yes	No
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pre-period CB shock	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Local labor market by year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Num. firms	7,601	7,712	7,425	5,456	7,601	7,712	7,425	5,456
Num. fixed effects	19,608	19,844	19,198	15,537	19,608	19,844	19,198	15,537
Num. observations	81,789	82,990	79,911	58,752	81,789	82,990	79,911	58,752
Adjusted R^2	0.8503	0.8506	0.8489	0.8543	0.8991	0.8990	0.8992	0.9008

Notes: Data are from the baseline sample of exporting firms. The table show regression coefficients on the firm and CB shocks variables interacted with an indicator for year greater than or equal to 2012. All outcomes are computed using the full set of workers in the firm-year. The regressions are analogous to the ones in Table 1, but changing the sample of CB units included in the regression. Standard errors are clustered at the CB level for the CB shock variable, and at the firm level for the firm shock variable.

Appendix Table 11: Estimation strategy for different parameters

Parameter	Description	Source
ζ	Elasticity of formal employment	Literature
η	Elasticity of labor supply to the firm	OLS estimation
$\{A_{k1}\}$	Amenity values of 1-digit sectors	OLS estimation
α	Curvature of productivity processes	Calibration
$\{\varphi_{g0}\}$	Minimum productivity of Pareto distributions	Model inversion
$\{b_r\}$	Outside option of workers in each r	Model inversion
$\{\beta_c\}$	Bargaining power parameters	Model inversion

Appendix Table 12: Estimates of preference heterogeneity

	Log average monthly pay				
	(1)	(2)	(3)	(4)	(5)
Log employment	0.2372	0.2368	0.2439	0.2307	0.2351
	(0.0108)	(0.0109)	(0.0065)	(0.0061)	(0.0065)
Year	Yes	No	No	No	No
Year-Region FE	No	Yes	Yes	No	No
1d sector FE	No	No	Yes	No	No
Year-Region-CBA FE	No	No	No	Yes	No
Year-Region-CBA-6d sector FE	No	No	No	No	Yes
Observations	1,243,640	1,243,640	1,240,627	1,240,627	1,240,627

Notes: Data are from labor market administrative records from Argentina. The sample is a panel of firm-years between 2012–2017 with 99% or more of their workers with a declared CBA code, and no workers with a declared wage below 40% of the wage floor. The table shows estimates of preference heterogeneity $1/\eta$ in the theoretical model. The dependent variable in all models is the log average monthly pay. The independent variable is the log of employment, computed in "full-time equivalent" workers by weighting part-time workers by 1/2. Columns show estimates changing the value of the fixed effects. Standard errors are clustered at the province by CBA level.

Appendix Table 13: Region-level data and 2011–2012 model estimates

Region	Centro (center)	Cuyo (west)	Norte (north)	Patagonia (south)
Private-sector workforce	5,099,128	399,917	837,599	204,902
Formal workforce	2,588,641	177,622	280,195	123,478
Share formal	0.5077	0.4441	0.3345	0.6026
W_r	0.8554	0.8510	0.8491	1.2820
V_r	1.0414	1.0360	1.0337	1.5607
b_r	0.9809	1.2640	2.0080	0.7474

Notes: Data are from the national household survey from INDEC and estimates from the structural model.

Appendix Table 14: Summary statistics of local labor markets

Variable	N	Mean	Std. Dev.	Min	Max
Unique regions	4				
Unique sectors	789				
Unique non-local CB units	322				
Unique local CB units	690				
Indicator region "Centro"	3,832	0.6221	0.4849	0.0000	1.0000
Indicator local CB unit	3,832	0.1822	0.3860	0.0000	1.0000
Indicator retail CB 0130/75	3,832	0.2132	0.4096	0.0000	1.0000
M_g	3,832	1.0000	4.1088	0.0035	180.2546
In 2011–2012:					
Mean wage (2010 ARS, 000s)	3,829	3.3043	1.2069	1.0729	22.4697
Mean wage floor (2010 ARS, 000s)	3,832	2.5800	0.7195	1.3168	11.1435
Share of firms bunching	3,832	0.2387	0.1538	0.0000	0.9952
Est. minimum productivity	3,832	3.0447	0.8507	1.5162	13.8511
In 2014–2015:					
Mean wage (2010 ARS, 000s)	3,828	3.3876	1.2875	1.1641	19.5031
Mean wage floor (2010 ARS, 000s)	3,832	2.6951	0.8296	1.1718	11.0538
Share of firms bunching	3,832	0.2614	0.1659	0.0013	0.9886
Est. minimum productivity	3,832	3.1617	0.9874	1.3308	13.4162

Notes: Data are from local labor market aggregates constructed using the administrative labor market data of Argentina. The table shows summary statistics of local labor markets in 2011–2012 and 2014–2015, dropping small local markets that appear in a single year.

Appendix Table 15: Effects of exporting shocks on aggregate revenue, survey sample

	Change aggregate revenue			
	(1)	(2)	(3)	(4)
Sectoral shock by Exporter	0.2238	0.1436	0.2475	0.2223
	(0.1192)	(0.0697)	(0.1381)	(0.1188)
Sectoral shock by Non-exporter	0.0849	0.0527	0.0689	0.0713
	(0.0564)	(0.0508)	(0.0577)	(0.0533)
Excluded CBA	None	Metal	Retail	Plastic
Exporter-specific intercept	Yes	Yes	Yes	Yes
R2	0.0510	0.0391	0.0524	0.0547
Observations	154	110	147	149
Number of firms	4,840	3,268	4,405	4,513

Notes: Data are from a sample of firms surveyed in the first wave of the *Encuesta Nacional de Dinámica del Empleo y la Innovación* (ENDEI). The table show estimates of exporting shocks on aggregate revenue at the 4-digit economic sector level on exporters and non-exporters. The baseline sample includes economic sectors with at least 4 exporting firms and 6 total firms. The sectoral shock is computed as follows. First, I compute the change in average log world import demand at the firm level between 2010 and 2012. Second, I define the sectoral shock as the average firm-level shock, weighting by employment in 2010, for all exporting firms. The change in aggregate revenue is computed as the log difference in the sum of revenue declared by surveyed firms in each exporter status by 4-digit economic sector cell. The Metal CBA has code 0260/75, the Retail CBA has code 0130/75, and the Plastic CBA has code 0419/05. The row "Number of firms" reports the number of firms used to compute aggregate revenue. Standard errors are clustered at the 4-digit sector level.

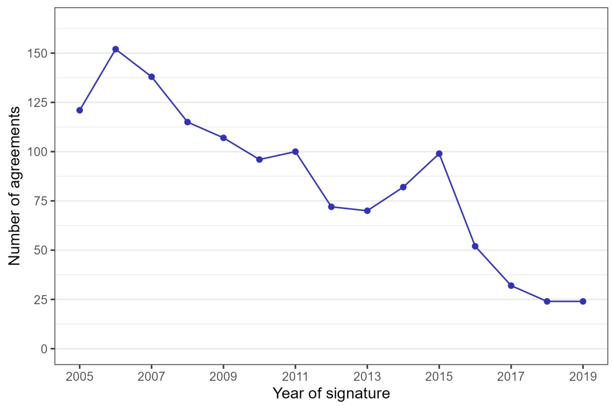
Appendix Table 16: Effects of CB shocks on log wages and log wage floors, aggregate data vs model-generated data

	Data, 2011 vs 2014			Model	
	Log wage (adj. part-time)	Log wage	Log wage floor	Log wage	Log wage floor
CB shock	0.0642	0.0797	0.0713	0.0186	0.0216
	(0.0438)	(0.0438)	(0.0454)	(0.0030)	(0.0123)
Share exporting empl. CB unit	Yes	Yes	Yes	Yes	Yes
Region by 4d by exporter FE	Yes	Yes	Yes	No	No
Region by exporter FE	No	No	No	Yes	Yes
Observations	2,337	2,341	2,338	1,238	1,238

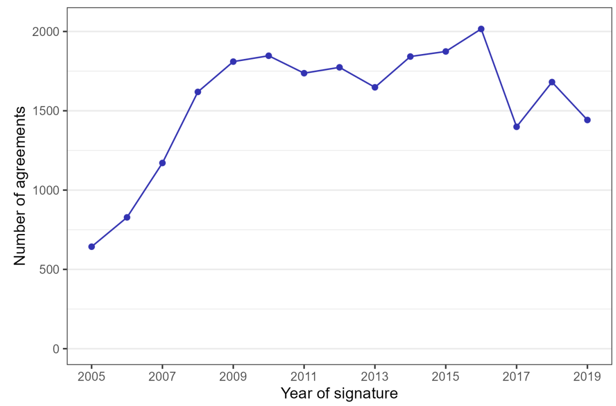
The table shows the effect of CB shocks on log wages and log wage floors, in the aggregate data and the model-generated data. The model is estimated using 2011–2012 data. I simulate shocks in the model so that changes in minimum productivities mimic the effects of exporting shocks on revenue at the local labor market level, and then re-compute the model equilibria using the new minimum productivities. Then, I regress the change in an outcome on the average local labor market shock at the CB level, using pre-period employment shares to weight the shocks. The model-based data excludes local labor markets covered by the retail CB unit, and those in CB units with less than 1 percent of employment in exporting firms. Standard errors clustered at the CB level.

Appendix Figure 1: The pace of negotiations, 2005–2019

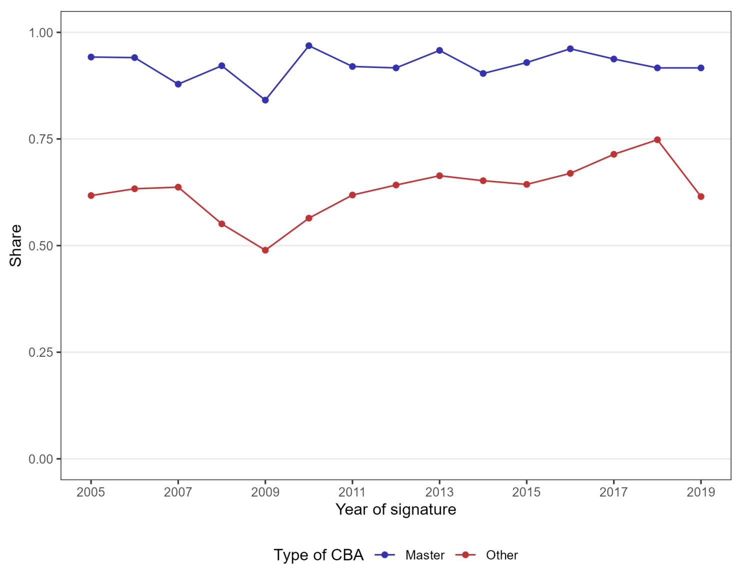
(a) Number of master CBAs



(b) Number of CBA alterations

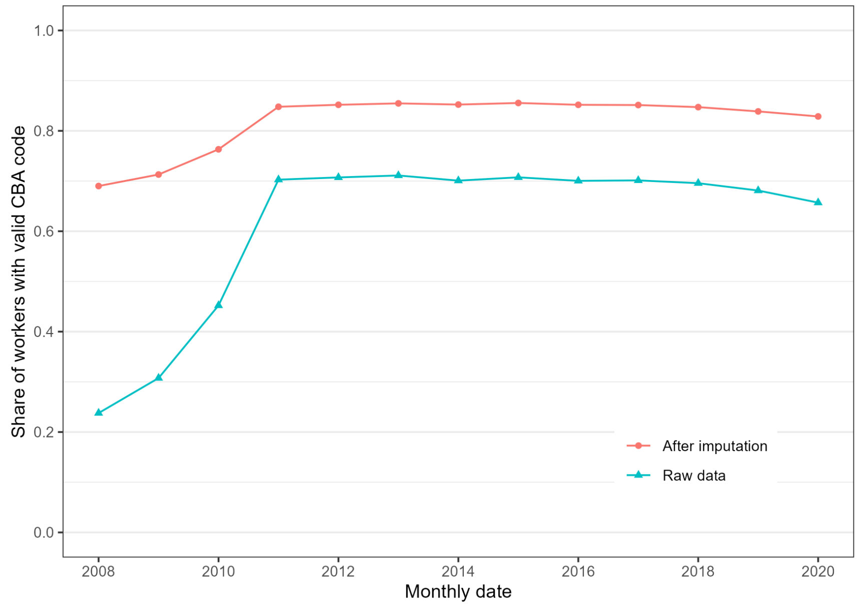


(c) Number of CBA that mention compensation



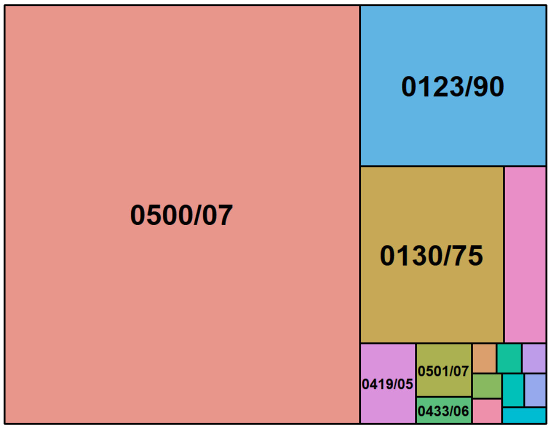
Notes: Data are from the public archive of Collective Bargaining Agreements. Panel (a) shows the number of master CBAs signed each year, Panel (b) shows the number of CBA alterations, and Panel (c) shows the share of each type of CBAs that contain the word "salario" as part of the description of their contents.

Appendix Figure 2: Share of workers with non-missing CB agreement code, raw data

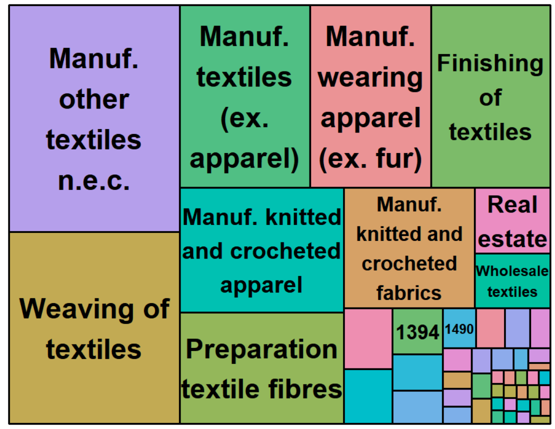


Notes: The figure shows the share of workers in the employer-employee dataset that can be matched to a valid CB agreement code.

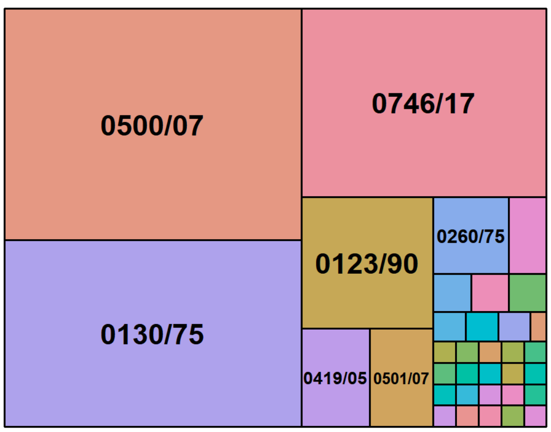
Appendix Figure 3: Illustration of heterogeneity in CBA coverage, textile industries



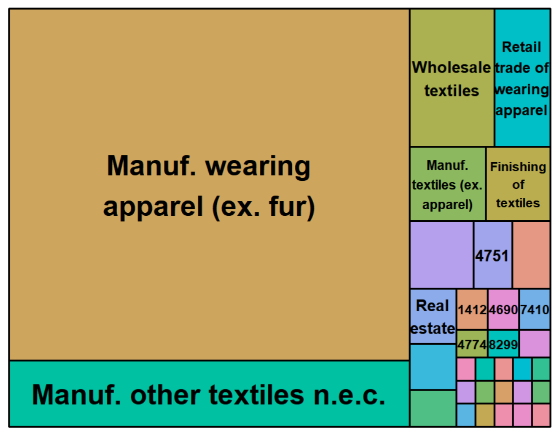
(a) Weaving of textiles



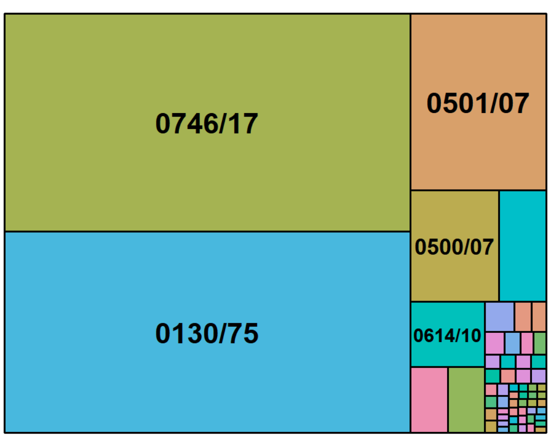
(b) CBA 0500/07



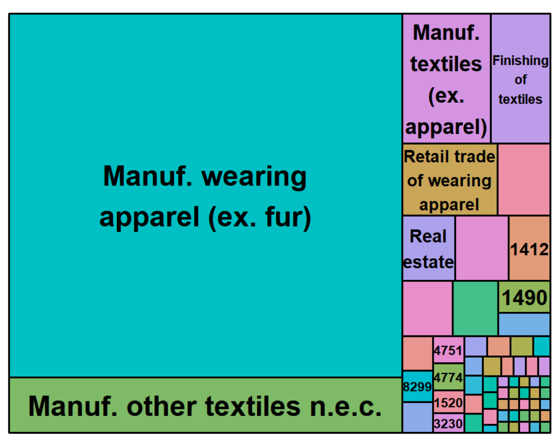
(c) Manuf. textiles (ex. apparel)



(d) CBA 0501/07



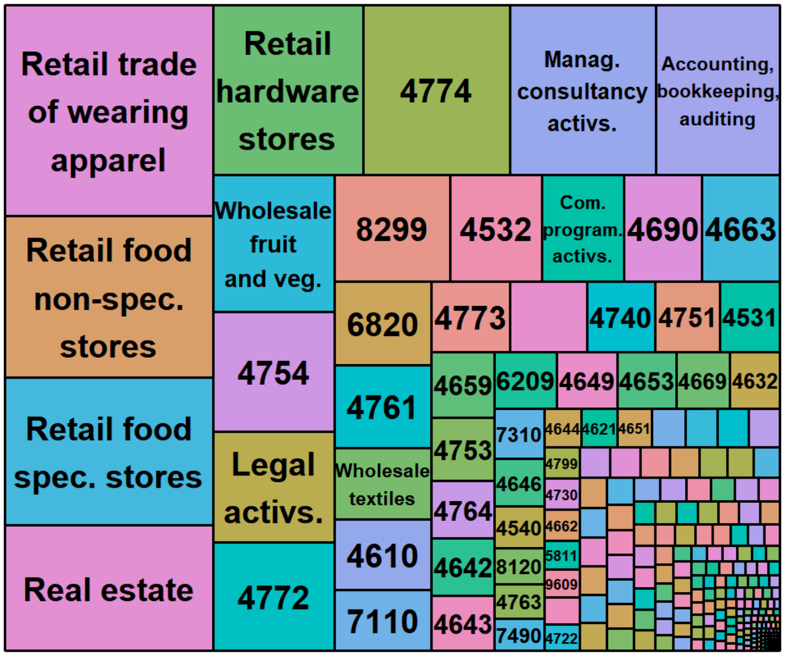
(e) Manuf. wearing apparel (ex. fur)



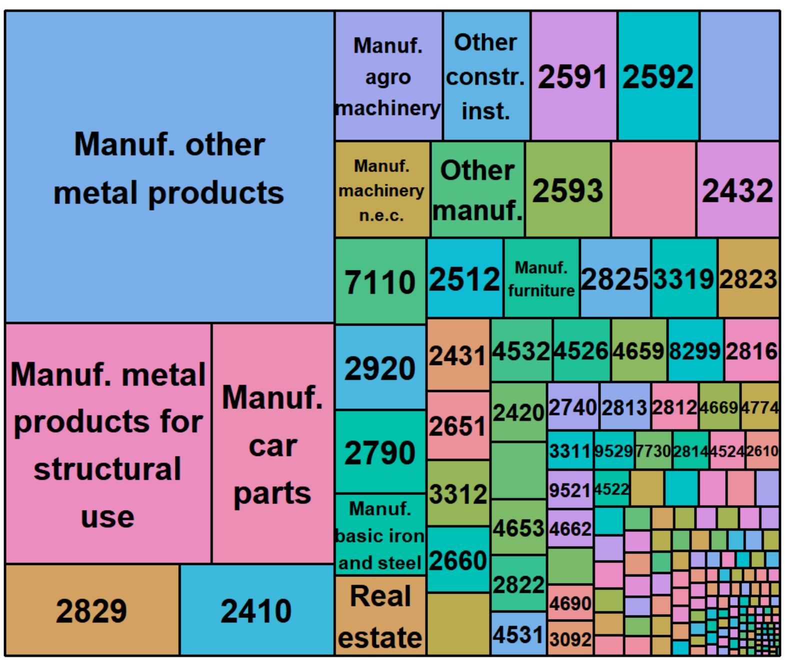
(f) CBA 0746/17

Notes: Data include all firms that declared workers in 2012 and were imputed a primary CBA code following the procedure described in Appendix B.4. Each box represents the sum of firms in the given economic sector or CBA, and the rectangles within each box represent the number of firms in each CBA, for the panels on the left, or the number of firms in each sector, for the panels on the right. CBA 0500/07 was signed by *Asociación Obrera Textil*, CBA 0501/07 was signed by *Sindicato de Empleados Textiles de la Industria y Afines*, and CBA 0746/17 was signed by *Federación Obrera Nacional de la Industria del Vestido y Afines.*

Appendix Figure 4: Illustration of heterogeneity in CBA coverage, selected CBAs



(a) CBA 0130/75: "Comercio" (retail trade)

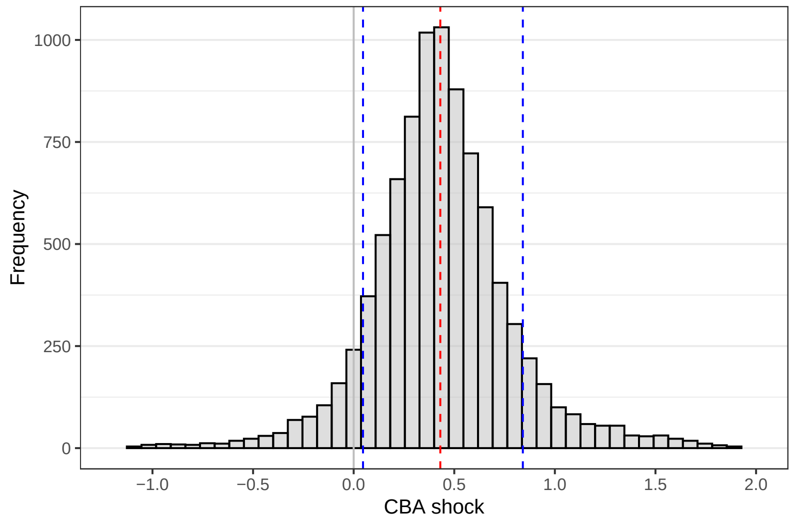


(b) CBA 0260/75: "Metalúrgicos" (metalworking)

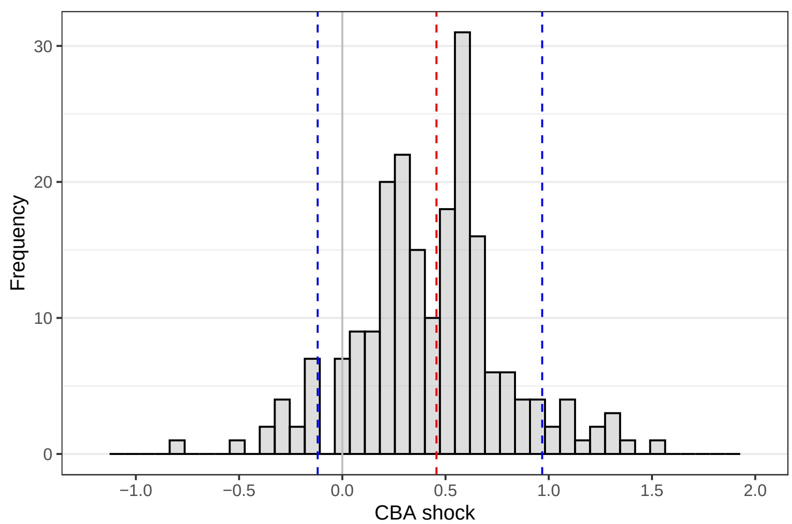
Notes: Data include all firms that declared workers in 2012 and were imputed a primary CBA code following the procedure described in Appendix B.4. The figure illustrates the different economic sectors that are linked to each CBA. Each box represents the sum of firms in the given CBA, and the rectangles within each box represent the number of firms in the given sector within that CBA.

Appendix Figure 5: Distribution of exporting shocks

(a) Firm shocks



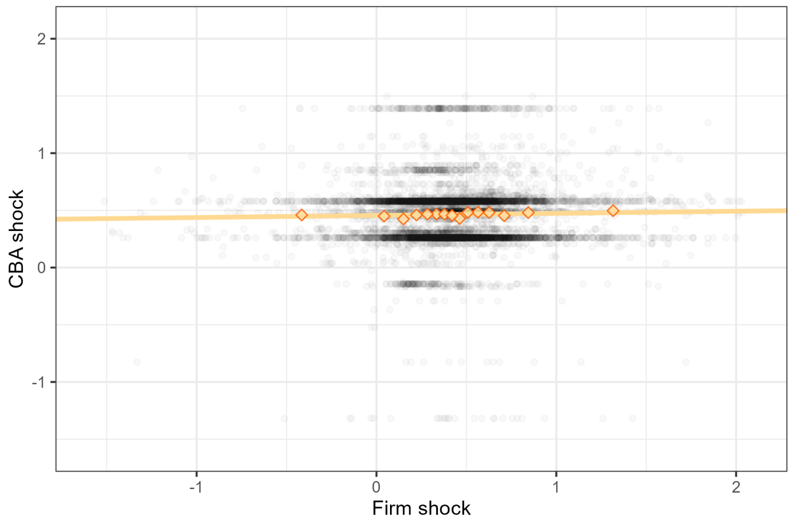
(b) CBA shocks



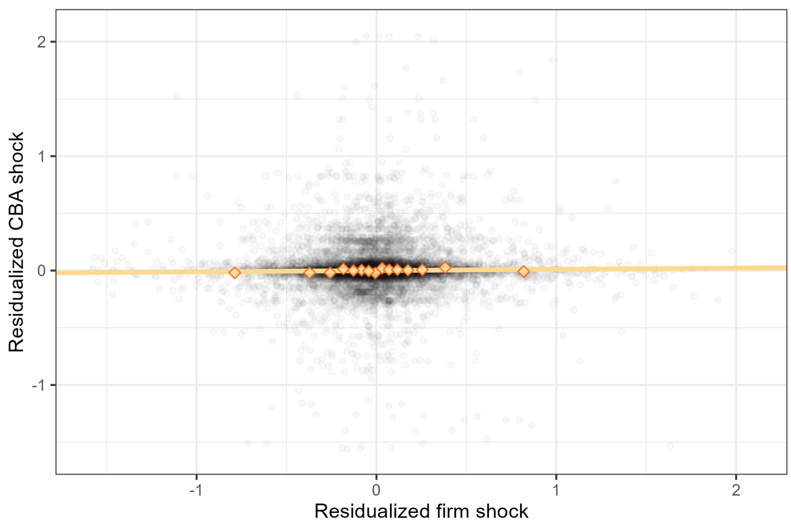
Notes: Data are constructed from a panel of firms that exported in 2011–2012. The figure illustrates the histogram of the firm and CBA shocks. The figure excludes values lower than -1 and larger than 2 to increase visual clarity. The red dotted lines in the middle shows the average shock, whereas the blue dotted lines on the sides show the 10th and 90th percentiles, respectively.

Appendix Figure 6: Correlation of exporting shocks to firms with exporting shocks to CB units

(a) Raw data

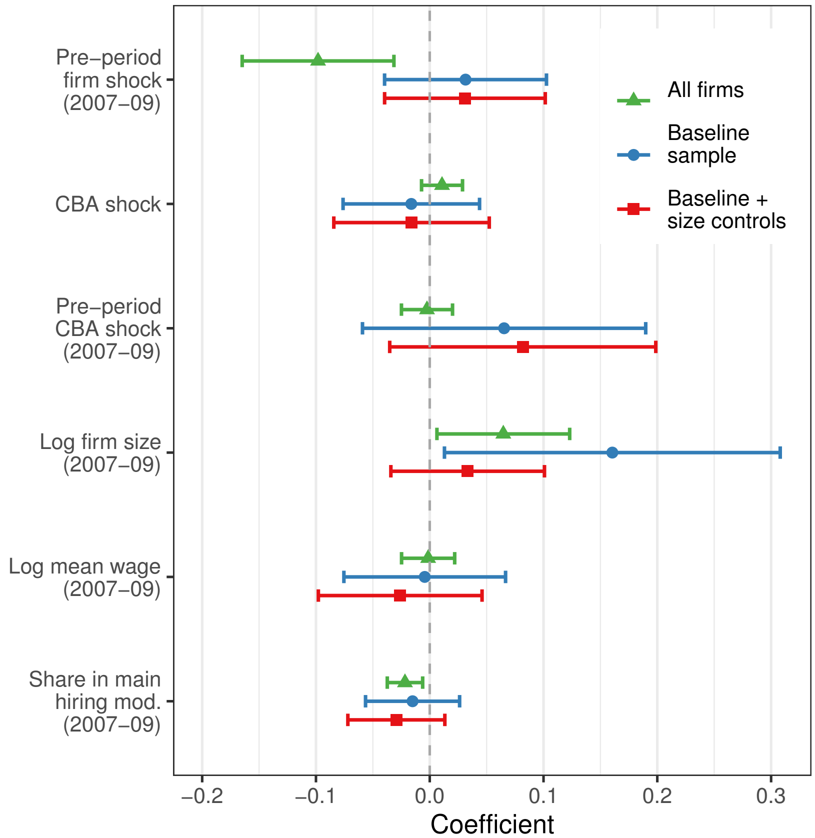


(b) Residualized on local labor market effects



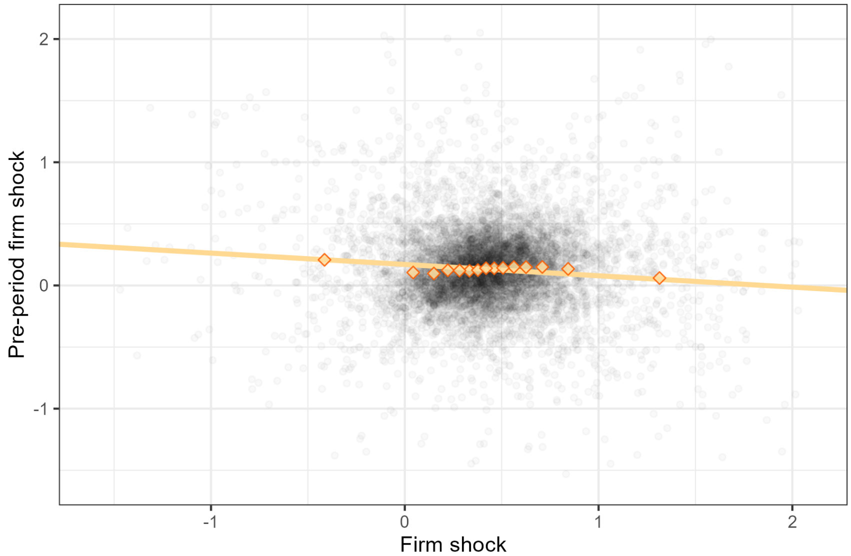
Notes: Data are constructed from a panel of firms that exported in 2011–2012. Panel (a) shows the correlation of firm shocks with CB shocks. Panel (b) shows the same correlation after residualizing for 4-digit sector by province fixed effects. The firm shock is defined as the difference between the 2012–2013 average to the 2009–2010 average in the value-weighted average world import demand for the firm, The CB shock is defined as the difference between the 2012–2013 average to the 2009–2010 average in the employment-weighted firm shock. To increase visual clarity Panel (a) excludes values lower than -1 and larger than 2 of both shocks, and Panel (b) excludes values lower than -1.5 and larger than 1.5 of both shocks. The blue line in both plots shows a non-parametric best fit.

Appendix Figure 7: Conditional correlation of firm shocks with baseline outcomes, firm-level cross-section



Notes: Data are constructed from a cross-section of firms that exported in 2011–2012. The figure shows the estimated coefficient on the firm shock on a regression of the outcome variable on the firm shock, controlling for 4-digit sector by providence fixed effects. Panel (a) shows the correlation of firm shocks, defined as the difference between the 2012–2013 average to the 2009–2010 average in the value-weighted average world import demand for the firm, with firm characteristics. Panel (b) shows the correlation of CB shocks, defined as the difference between the 2012–2013 average to the 2009–2010 average in the employment-weighted firm shock, with CB characteristics. The figure excludes values lower than -1 and larger than 2 of the CB shock to increase visual clarity. Standard errors are clustered at the CB level for the CB shock variables.

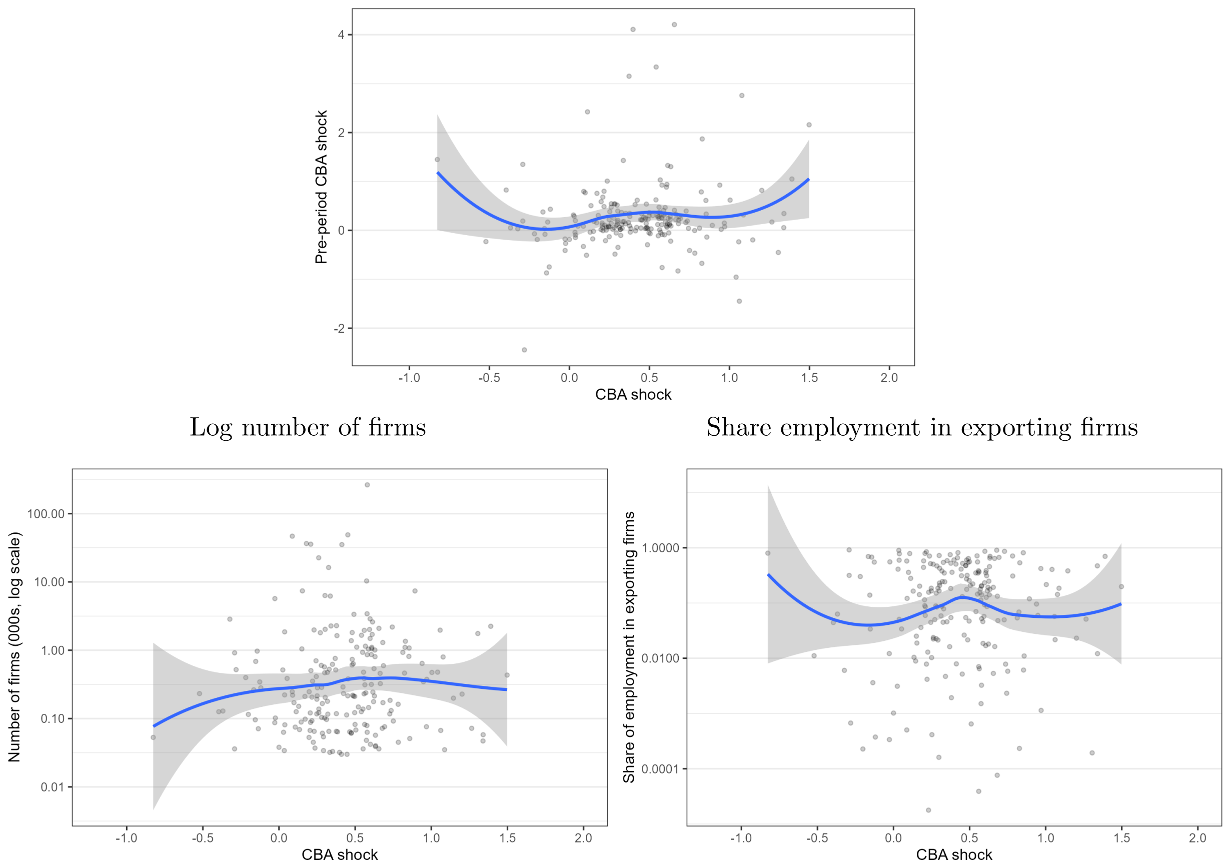
Appendix Figure 8: Auto correlation of exporting shocks to firms



Notes: Data are constructed from a panel of firms that exported in 2011–2012. The figure shows the correlation of firm shocks, defined as the difference between the 2012–2013 average to the 2009–2010 average in the value-weighted average world import demand for the firm, with an analogous firm shock computed as the difference between 2009–2010 and 2007–2008. The blue line in both plots shows a non-parametric best fit.

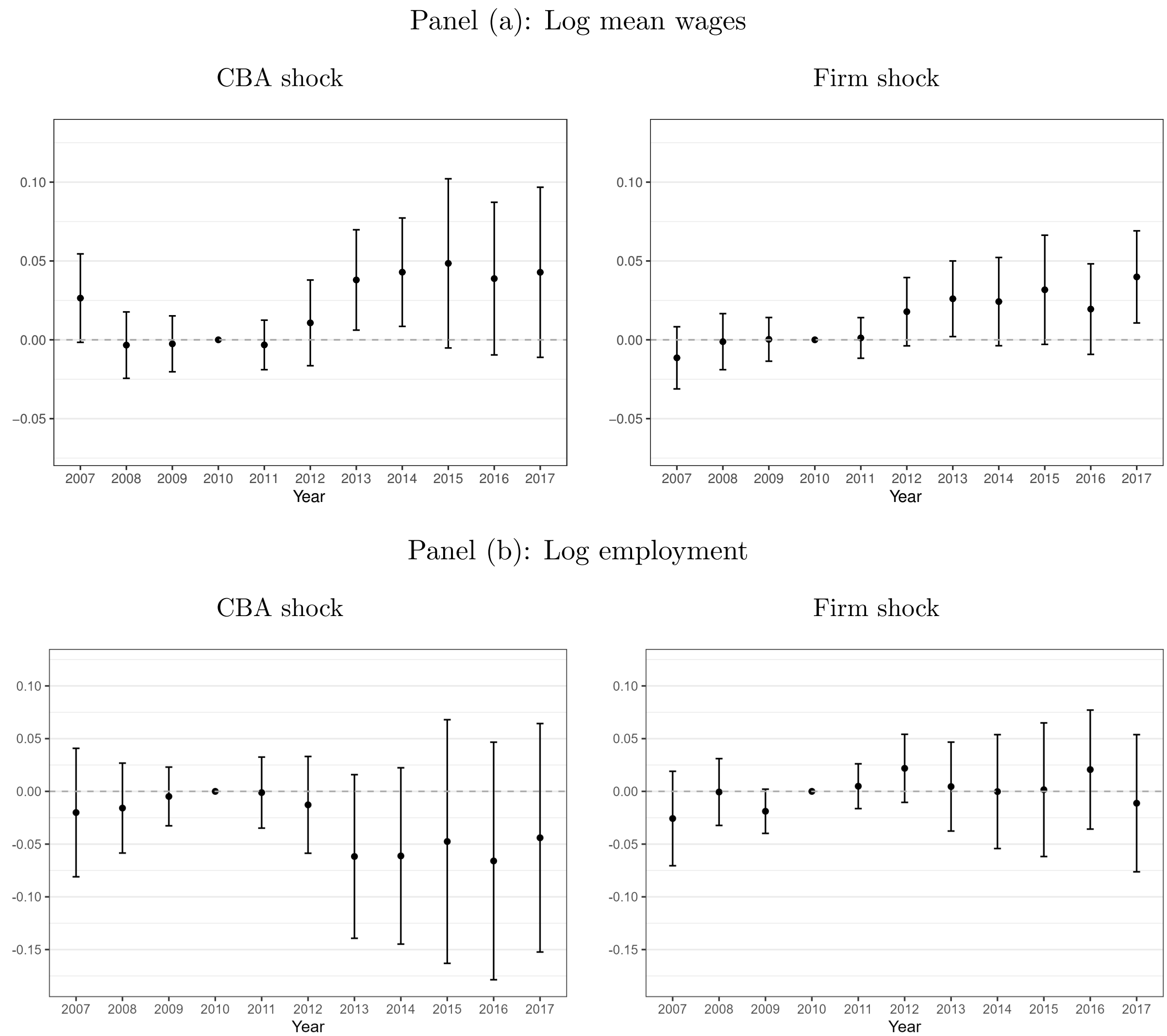
Appendix Figure 9: Correlates of exporting shocks to CB units with observables

Share employment in exporting firms



Notes: Data are constructed from a panel of firms that exported in 2011–2012. The figure shows a scatter plot of the CB unit shock with CB unit-level observables. Panel (a) uses the pre-period CB shock, constructed by differencing the proxy z_{jt} between 2008–2009 and 2008–2007. Panel (b) uses the number of firms. Panel (c) uses the share of employment in exporting firms. The blue line in both plots shows a non-parametric best fit.

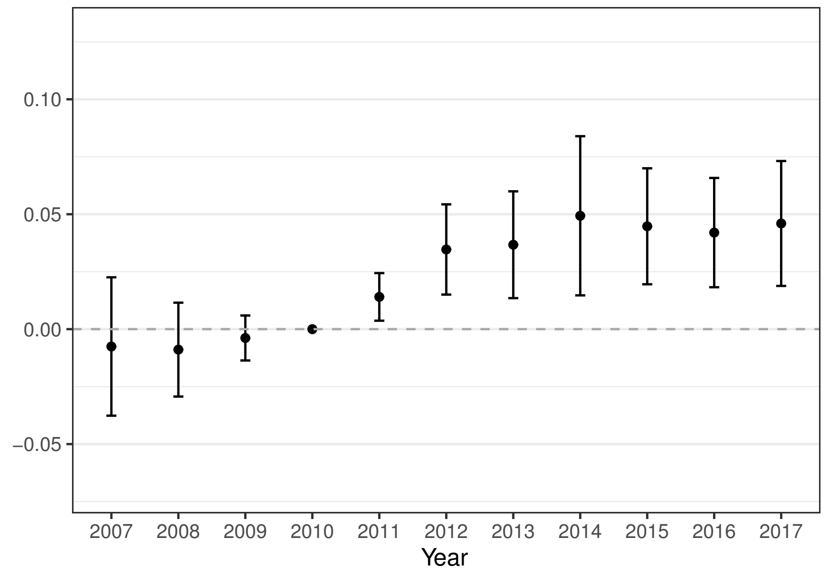
Appendix Figure 10: Effect of exporting shocks on mean wages and employment, excluding retail CBA



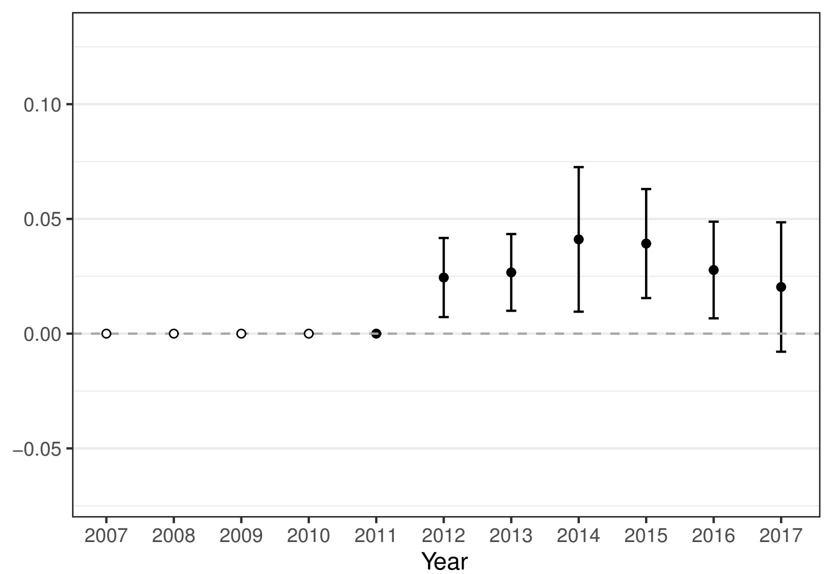
Notes: Data are from the baseline sample of exporting firms, excluding firms covered by the retail CBA 0130/75. The figure shows the dynamic effects of firm and CBA shocks on log mean wages and log employment, interacting the shocks with year dummies and omitting the year 2010. The construction of the figure is analogous to Figure 4. Standard errors are clustered at the CBA level for the CBA shock variable, and at the firm level for the firm shock variable.

Appendix Figure 11: Effect of exporting shocks to CB units on exporting and non-exporting firms

(a) Log mean wages



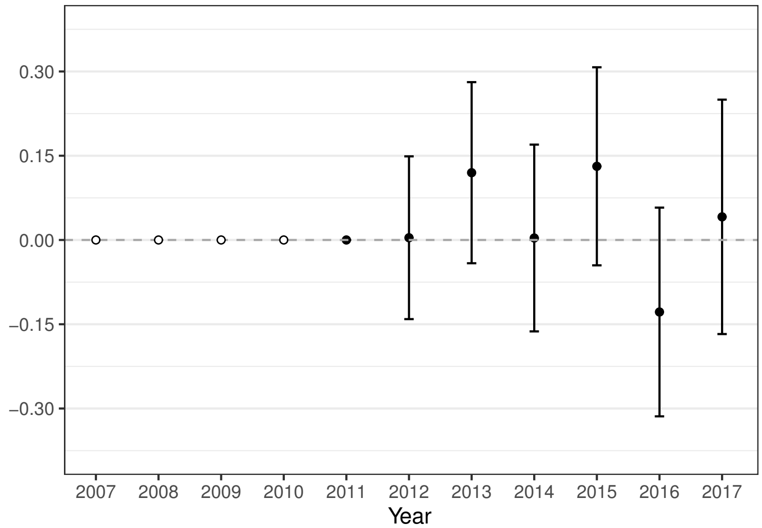
(b) Log mean wage floor



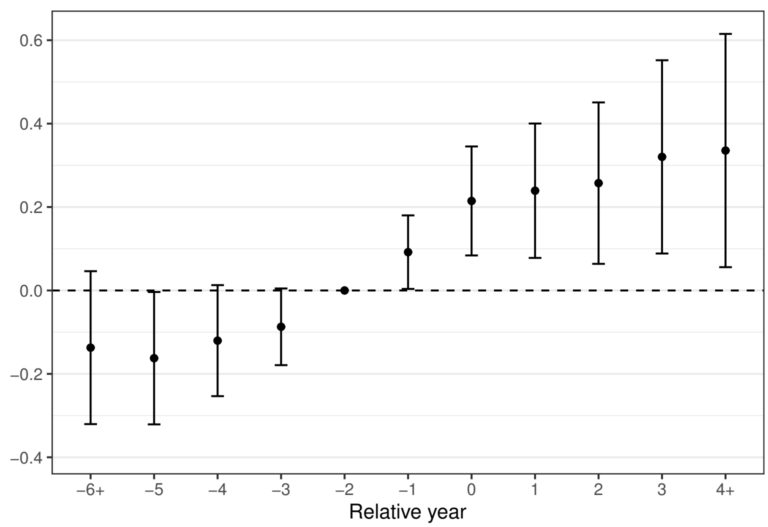
Notes: Data are from a panel of firms that are covered by an exporting CB in 2011–2012. The sample includes firms smaller than 500 employees at baseline, firms in CB units with more than 30 firms in 2011, and firms that were active in 2007 and 2009. The figure shows estimates of the effects of CB shocks on mean wages and mean wage floors. Estimation is done using a difference-in-differences strategy as in Figure 4 but excluding the firm shock. Standard errors are clustered at the CB unit level.

Appendix Figure 12: Effect of firm shocks on log value exported

(a) Difference in differences strategy



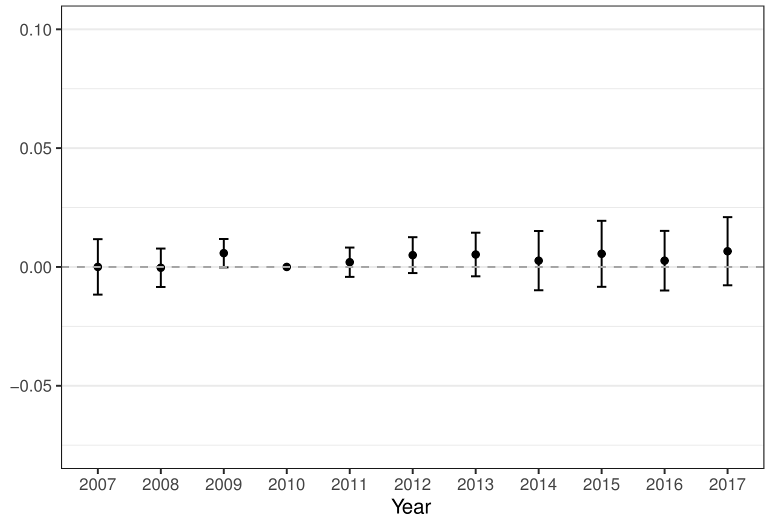
(b) Panel event-study strategy



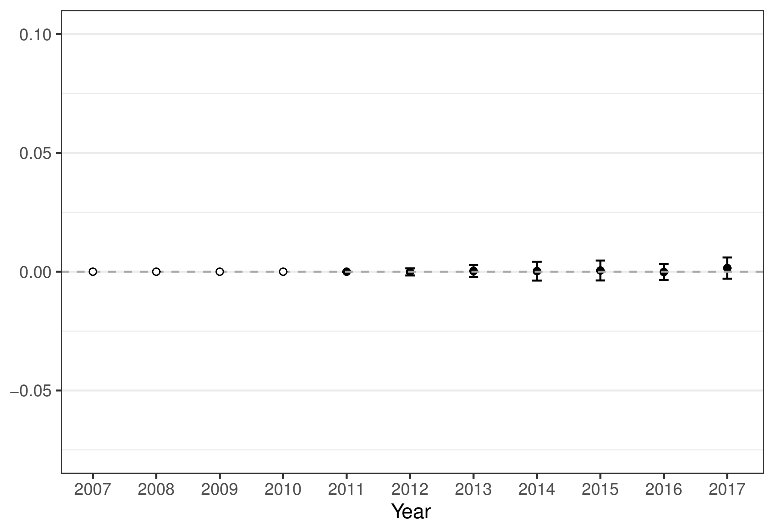
Notes: Data are from a panel of firms that exported in 2011–2012. For the DiD the sample corresponds to the baseline estimating sample. For the panel event-study the sample includes firms that had on average between 1 and 500 employees in 2009–2010, were covered by CB units with at least 30 firms in 2011, and exported in all years between 2011 and 2019. Both regressions include the following controls: firm fixed effects, 4-digit sector by province by year fixed effects, and 2-digit sector by size categories (1-9, 10-24, 25-99, and 100-500) by year fixed effects.

Appendix Figure 13: Effect of exporting shocks to CB units, placebo network exercise

Log mean wage



Log mean wage floor

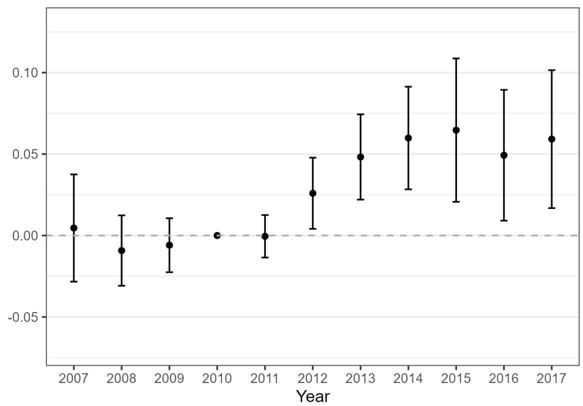


Notes: Data are from a panel of firms that exported in 2011–2012. The figure shows estimates of placebo shocks to CB units constructing a placebo network by randomly shifting the CB agreement code across firms within 1-digit sector and province. The top figure shows the effect of the place CB shock on log mean wages, and the bottom figure shows the effect on the log mean wage floor. Estimation is done using a difference-in-differences strategy, as in Figure 4. The white dots indicate years for which data are not available. As a result, both estimates control for the firm-level shock. Standard errors are clustered at the CB unit level.

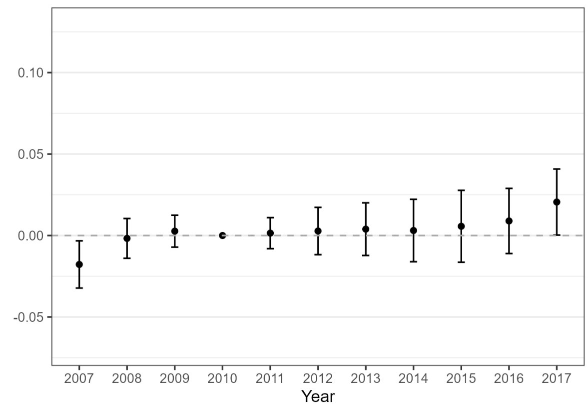
Appendix Figure 14: Effect of exporting shocks on wages, not excluding firms with extreme values of the pre-period shock

Panel (a): Log mean wages

CB shock

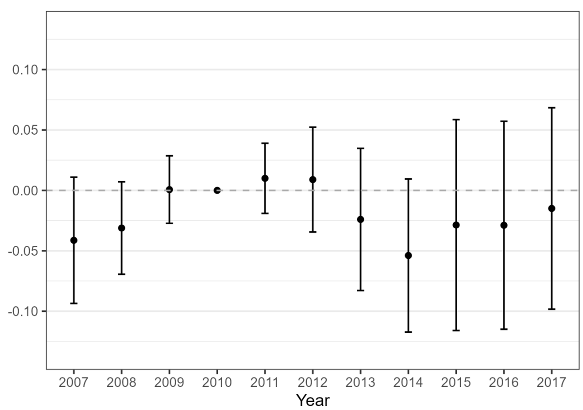


Firm shock

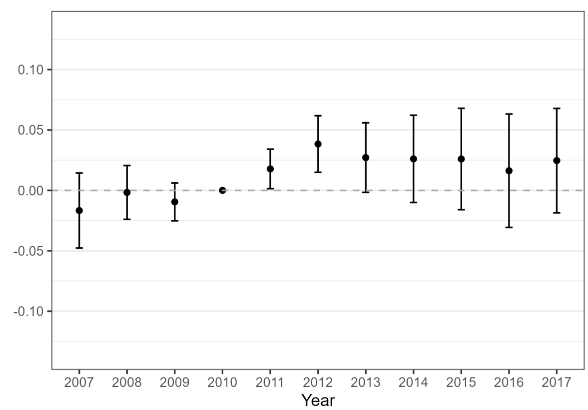


Panel (b): Log employment

CB shock



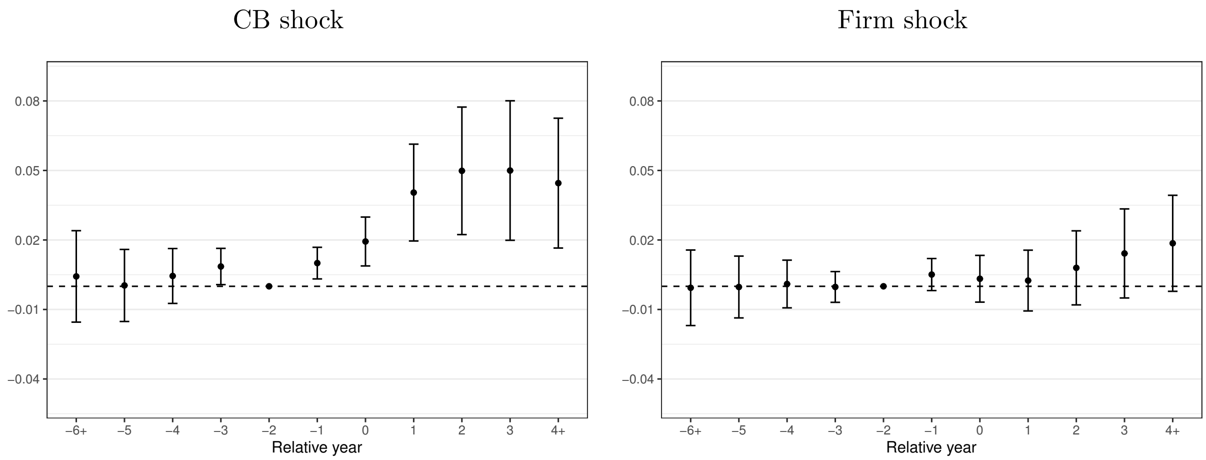
Firm shock



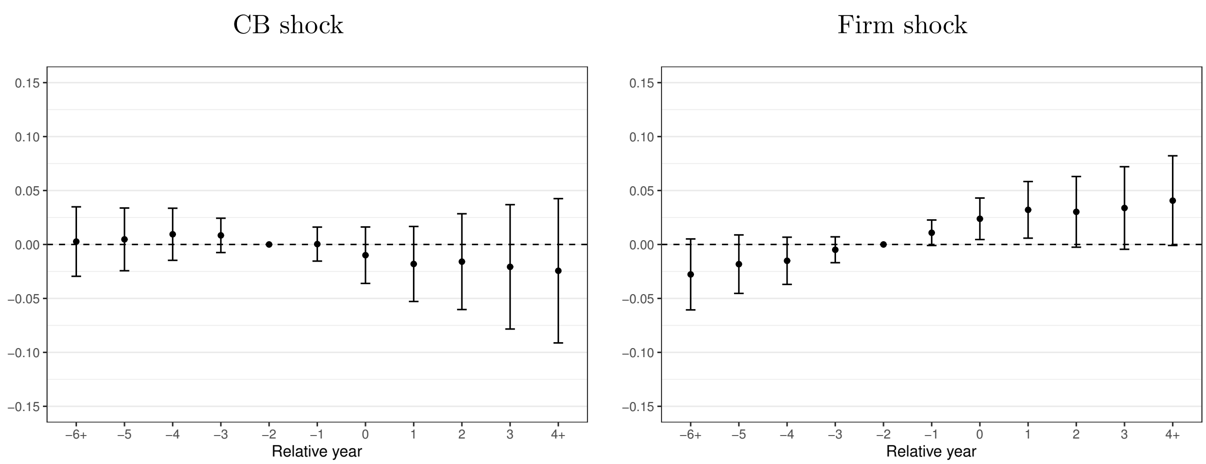
Notes: Data are from a panel of firms that are covered by an exporting CB in 2011–2012. The figure shows estimates of the effects of CB and firm shocks on log mean wages in Panel (a) and log employment in Panel (b). Estimation is done using a difference-in-differences strategy as in Figure 4 but keeping firms with extreme values of the pre-period shock. Standard errors are clustered at the CB unit level.

Appendix Figure 15: Effect of economic shocks on wages and employment, linear panel event-study

Panel (a): Log mean wages



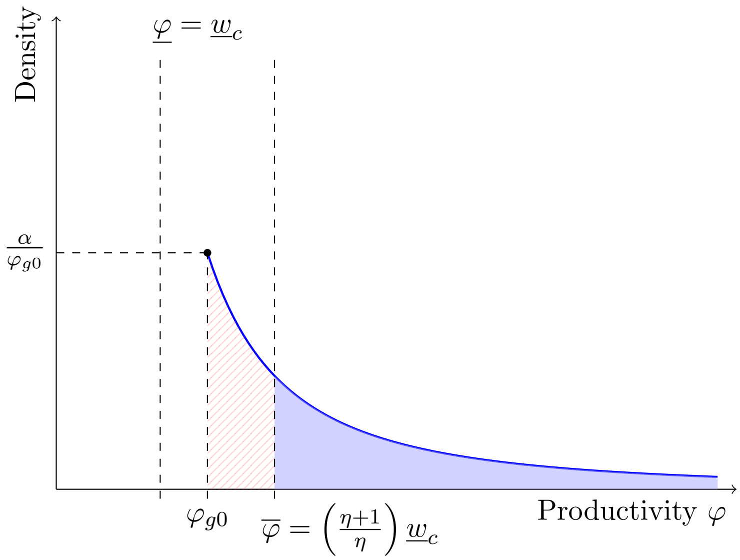
Panel (b): Log employment



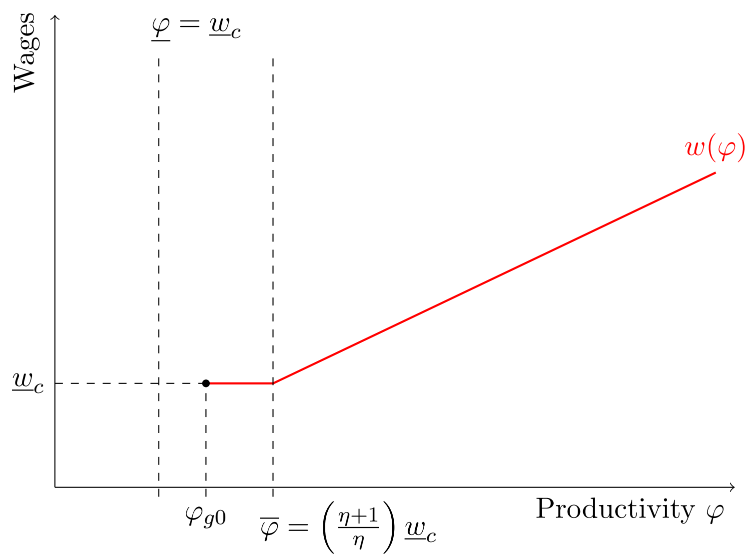
Notes: Data are from a panel of firms that exported in 2011–2012, had on average between 1 and 500 employees in 2009–2010, and were covered by CB units with at least 30 firms in 2011. The figure shows the effects of a CB shock and a firm shock on average monthly pay. The firm shock is defined as the value-weighted average of log world import demand (WID) of the products the firm exports at baseline, using 2011–2012 exported value as weights. The CB shock is defined as the employment-weighted average firm shock, using 2011 employment weights. The regressions include the following controls: firm fixed effects, 4-digit sector by province by year fixed effects, and 2-digit sector by size categories (1-9, 10-24, 25-99, and 100-500) by year fixed effects. Standard errors are clustered at the CB unit level for the CB shock, and at the firm level for the firm shock.

Appendix Figure 16: Illustration of firms productivity distribution

(a) Share of firms bunching

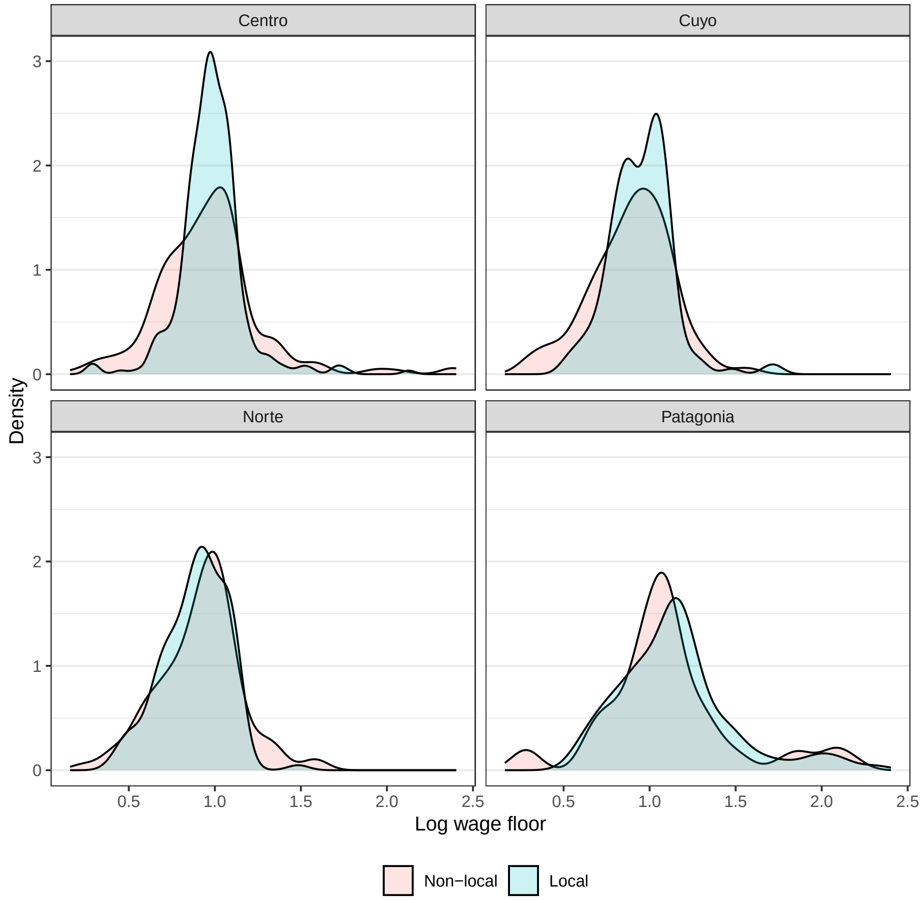


(b) Wages



Notes: The figure illustrates the productivity distribution of firms in local labor market g with binding wage floor $\underline{w}_c$, shape productivity parameter α, and minimum value φ_{g0}.

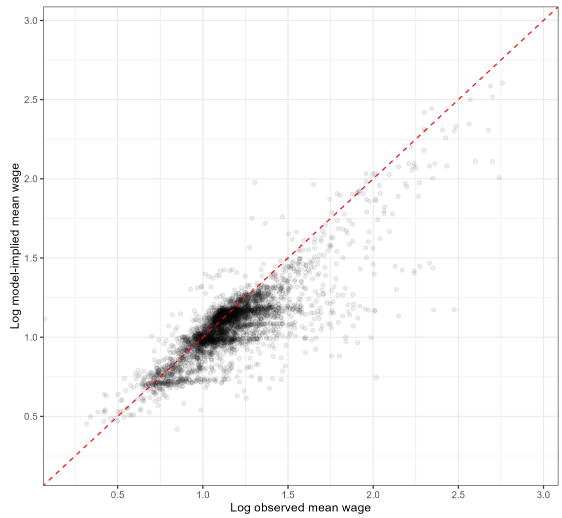
Appendix Figure 17: Log wage floors across CBAs by region, 2014–2015 data



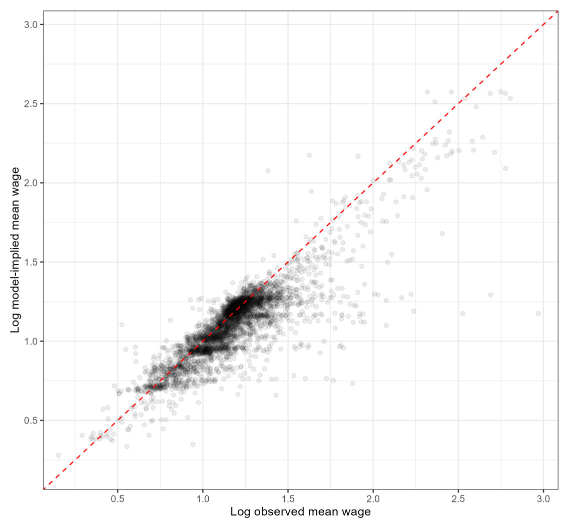
Notes: The figure shows the distribution of log mean wage floors in each of the four regions used in the analysis, splitting by whether the CBA is local or not. The mean wage floors are estimated using the estimated wage floors for each CBA category, as explained in Appendix F.3, using the 2014–2015 data.

Appendix Figure 18: Correlation between average wages in the data and in the model

(a) 2011–12



(b) 2014–15

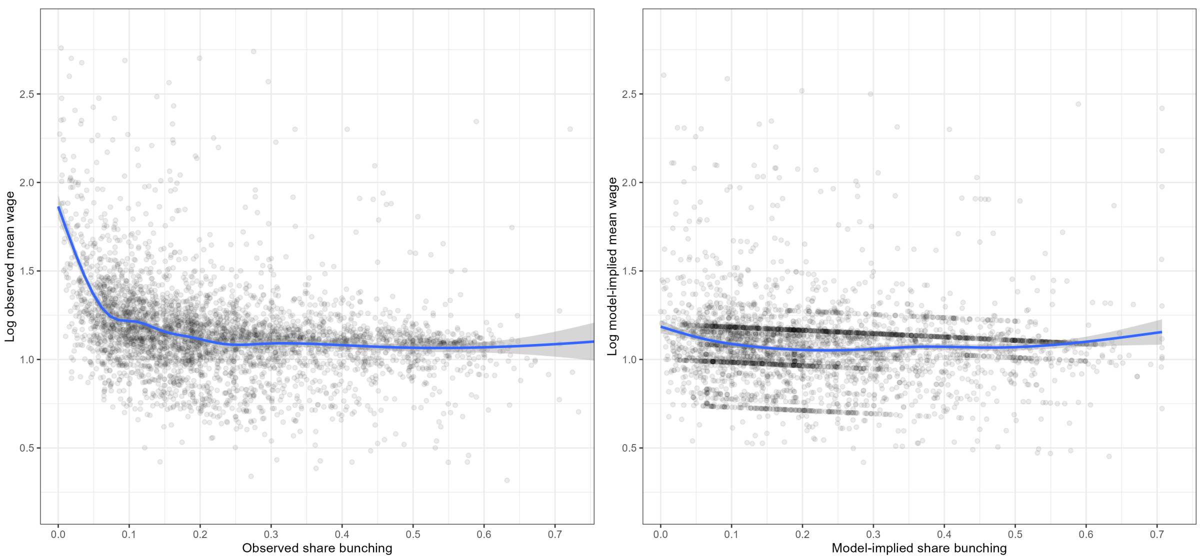


Notes: The figure shows a scatter plot of observed mean wages versus model-implied mean wages in each local labor market.

Appendix Figure 19: Correlations between different objects in the data and in the model, for 2011–2012

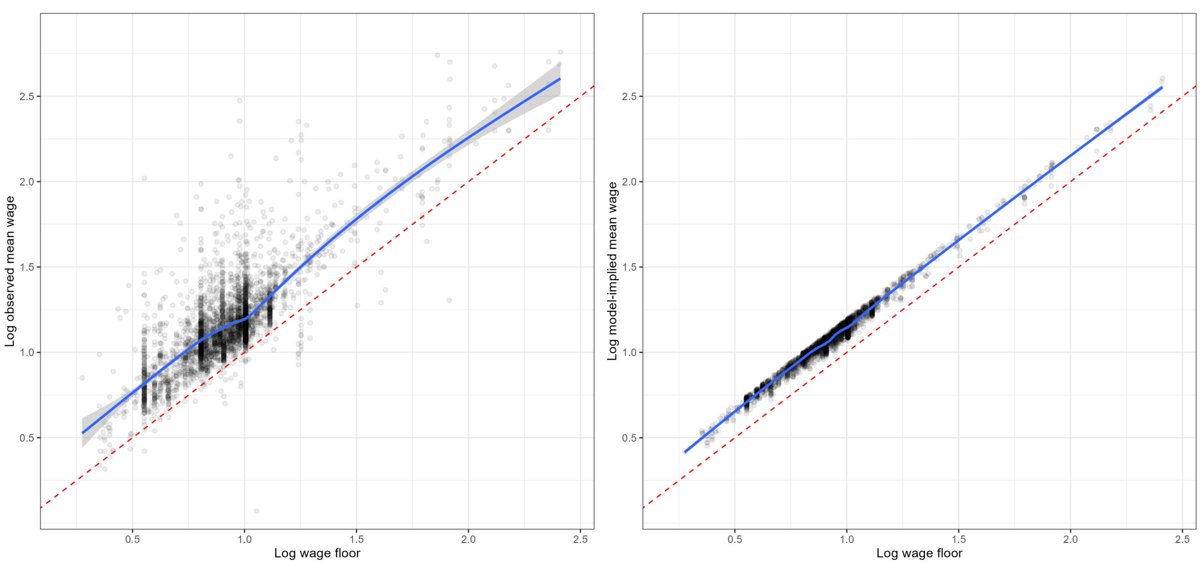
Share of firms bunching and average wage

(a) Data (b) Model



Wage floor and average wage

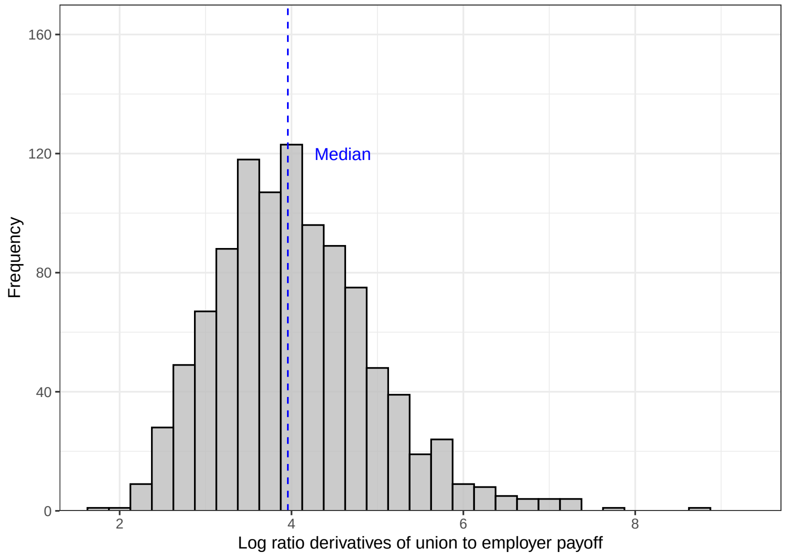
(c) Data (d) Model



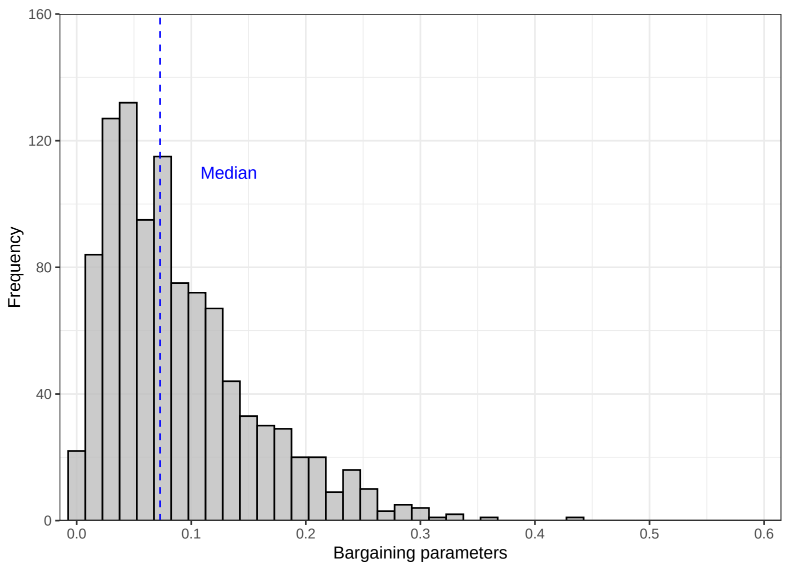
Notes: The figure shows a scatter plot of different objects across local labor markets. The top row correlates the share of firms bunching at the wage floor and the log of the average wage. The bottom row correlates the wage floor and the log of the average wage. The left column shows the data, the right column shows the model.

Appendix Figure 20: Estimates of bargaining power parameters

(a) Ratio of derivatives of objective functions



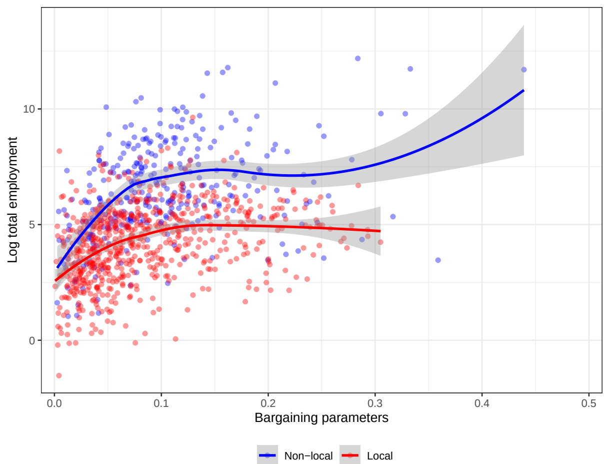
(b) Estimates of bargaining parameters



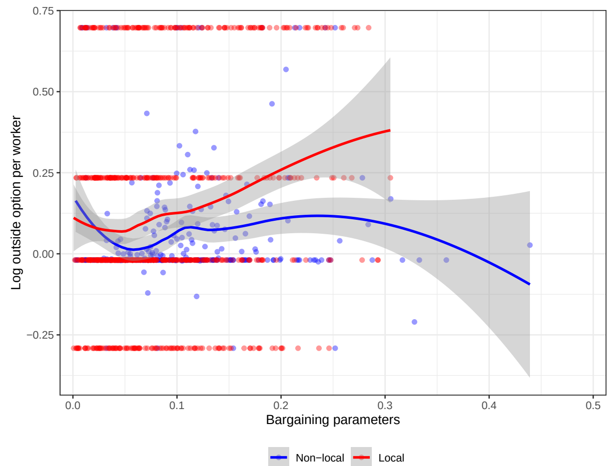
Notes: The figure shows model estimates. Panel (a) shows the estimated ratio of derivatives of the union objective function and the employer association objective function, both with respect to the wage floor. Panel (b) shows the estimated bargaining parameters. I exclude the estimates for the retail CBA 0130/75.

Appendix Figure 21: Correlations of estimated bargaining parameters with observables

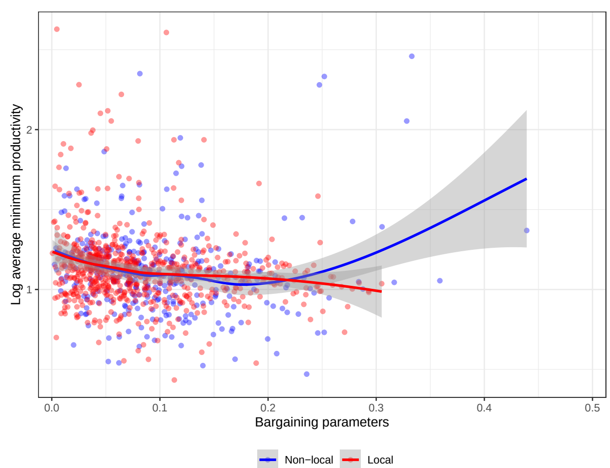
(a) Employment



(b) Outside option

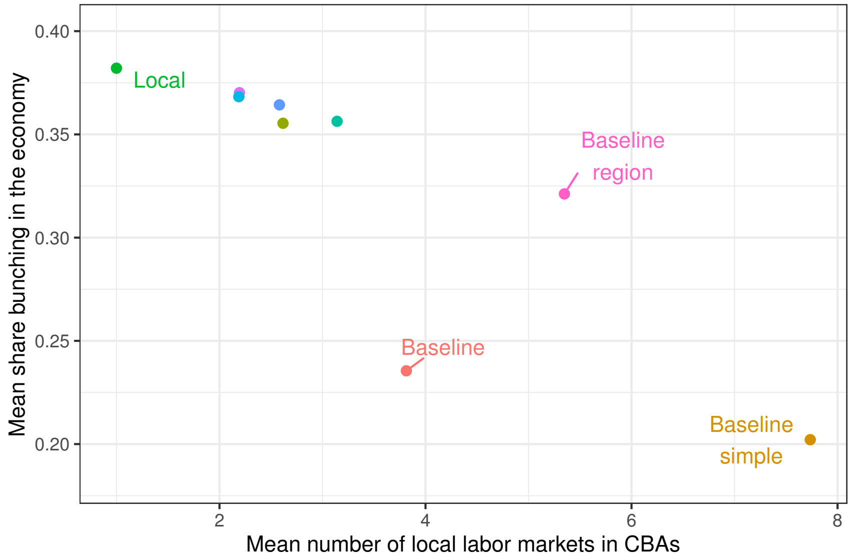


(c) Productivity



Notes: The figure shows the relationship between estimated bargaining parameters and employment (panel a), the average outside option (panel b), and the average productivity of the local labor markets it covers (panel c). The scatter is colored according to whether the CB unit is local or not.

Appendix Figure 22: Centralization of bargaining and shock propagation



Notes: The figure shows the correlation between the average share of firms bunching across local labor markets for CB networks with different levels of centralization of bargaining. The measure of centralization is the average number of local labor markets per CB unit. The correlation is computed using the model-generated data. The figure excludes local labor markets that correspond to the retail CBA at baseline and with less than 5% of employment in exporting firms.