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

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Abstract

I study the role of collective bargaining, a prevalent wage-setting institution in many countries, in determining the effects of economic shocks on workers and 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 product demand and to study how these shocks propagate through the collective bargaining network. My findings indicate that a shock equivalent to a 10% rise in firm revenue leads to a 1.5% increase in wages, and a shock equivalent to a 10% rise in average revenue of firms under the same agreement leads to a 4.3% increase in wages. 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 a general equilibrium model of the labor market with collective bargaining and firm heterogeneity to quantify how the degree of centralization of bargaining affects the propagation of shocks. The estimated model indicates that the degree of shock propagation is hump-shaped in the degree of centralization, with highly decentralized or highly centralized bargaining structures leading to less propagation than intermediate levels of centralization.

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

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1 Introduction

Collective bargaining (CB, for short) establishes common provisions for workers, such as wage floors, across all firms covered in a bargaining unit. CB can therefore influence how wages respond to changes in the economic conditions of employers. In Europe, for example, differential responses of national labor markets to the Great Recession and the rise of import competition from China have been linked to differences in bargaining institutions (e.g., Ronchi and di Mauro 2017; Barth et al. 2023). Understanding these responses is, in turn, important for the many public policies that seek to mitigate the effect of shocks on workers.[1] In the US, discussions about bargaining institutions have gained traction in recent years, and new bargaining policies have already been implemented.[2] These endeavors require and understanding of the trade-offs involved in different bargaining structures. While many papers examine how economic shocks, such as changes in product demand to firms, affect workers' wages (e.g., Van Reenen 1996; Autor et al. 2013) and propagate across firms and regions (e.g., Giroud et al. 2021; Adão et al. 2022), there is little direct evidence on the role of CB in mediating these effects.

Typically, CB defines a network of firms, with two firms connected in the network if they fall under the same CB unit and therefore share the same commonly bargained provisions. The structure of the CB network differs widely across countries, with some characterized by large sectoral CB units, and others by employer-level bargaining (Bhuller et al. 2022). When economic shocks affect firms in a particular region or sector, these different forms of CB network seem likely to respond differently.[3] For instance, if firms in an affected region are connected to firms in another region via CB, then updated negotiations in the CB unit may result in wage changes in the unaffected region as well. This could be a cause for concern if it results in low-wage regions covered by high wage floors that are not aligned with local conditions (Boeri et al. 2021), however, it could also be desirable if it dissipates the effects of concentrated shocks, effectively sharing the risk of shocks across workers and firms.

Studying the role of the CB network in determining the responsiveness of wages to economic shocks is challenging for several reasons. First, it requires detailed information on the CB network, which is not usually available in administrative datasets. Second, it requires measurable and exogenously determined shocks to employers. Finally, it requires an economic model where firms exposed to shocks are subject to common provisions negotiated by a CB network.

In this paper, I study how CB 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 plausibly exogenous product-demand shocks exploiting changes in

[1] See, for example, the US Trade Adjustment Assistance program or the EU Globalisation Adjustment Fund.

[2] See, for example, the recent California law granting bargaining power to fast-food workers. Washington Post (2022) notes that the "California law is widely seen as a step toward sectoral bargaining."

[3] As noted by Katz and Autor (1999, pp. 1540), "the same labor market shocks [...] may have different impacts on the wage structure depending on how unions and government regulations affect wage setting."

international demand for exported products, and compare the evolution of outcomes across firms that are shocked directly or via their CB unit. Second, I develop and estimate a structural model where firms in different regions and economic sectors are connected by a CB network, and use it to study the incidence of shocks on wages under counterfactual networks.

The case of Argentina in the aftermath of the Great Recession provides an excellent case study for several reasons. First, CB is widespread in the country, with 93% of workers covered by some agreement in 2014 (Ministerio de Trabajo, Empleo y Seguridad Social 2023). As in several other countries, agreements establish minimum working conditions for covered workers and firms.[4] Second, an unexpected shift in international demand for Argentina's exports in the aftermath of the Great Recession makes for a compelling natural experiment to study the role of CB in the propagation of shocks. Finally, due to the country's legal structure, CB units are not entirely determined by region or economic sector, resulting in an idiosyncratic network that allows me to compare otherwise similar firms that are nevertheless part of different CB units.

To construct product-demand shocks I leverage variation in world import demand arising from granular country-product pairs exported by Argentine firms in 2009–2013. During this period, Argentina underwent a significant shift in international demand for its exports, primarily due to unexpected recessions and subsequent recoveries of varying magnitudes across countries following the Great Recession. Following Garin and Silvério (2023), I maintain that this variation is exogenous to firms and unions, and use it to study the effects of shocks. Firms are exposed to changes in world import demand via the share of their value exported to each country-product, as reflected in Argentine Customs data. CB units are also exposed to product-demand changes via their employment shares in firms that export to each country-product. I define shocks to firms and CB units as the weighted average of the changes in world import demand, weighting by the appropriate exposure share to each country-product.

I use administrative data on firms' wages and employment and a difference-in-differences strategy to estimate the effects of shocks. To identify the effect of firm shocks I compare the evolution of outcomes for firms in the same province and economic sector that are subject to a similar CB shock but a different firm shock. I proceed analogously to identify the effects of CB shocks. The key assumption is that, within province and sector cells, growth in world import demand (WID) affected firms because of the resulting changes in their product demand and in the outcomes of bargaining, and not because growing firms sorted into markets with trending WID or were affected by changes in WID through other connections instead of their CB unit. In an appendix, I show that these assumptions can be cast in terms of conditional quasi-random assignment of product-demand shocks, as in recent work by Borusyak et al. (2022b). Several tests support the validity of this assumption in my setting.

My main estimates reveal that a 10% increase in world import demand at the firm level increases wages by 1.73% (SE=1.17%), and a 10% increase in average world import demand at the CB unit level increases wages by 4.82% (SE=1.83%). Combining these results with evidence

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

from a survey of businesses, I estimate that a shock equivalent to a 10% increase in average CB revenue would increase wages by 4.4% among covered firms. I find that these effects are stronger for larger CB units. I use the administrative data to construct a novel dataset of wage floors, the main outcome of negotiations, by detecting bunching in the distribution of wages within CB units and occupation categories. Then, I estimate my models using the wage floor as outcome, and find that wage floors increase by a similar magnitude as paid wages following a CB shock. I consistently find that wage floors respond to CB shocks but not to firm or sectoral shocks.

I then delve into the effects of product-demand shocks on employment. Importantly, theory suggests that a wage floor should result in heterogeneous employment responses across firms with different productivity levels (Ahlfeldt et al. 2022). Low productivity firms are constrained by the wage floor, and so they should respond to CB shocks by decreasing employment as they move along their labor demand curve. Medium productivity firms may increase employment if, at their pre-shock wage, they were exercising monopsony power to lower wages below the marginal product of labor. As a proxy for firm productivity, I explore effects for firms with different levels of pre-period wage. I find that low-wage firms in CB units that experience growth in world import demand decrease employment, consistent with this theory. I also find evidence of positive employment effects for medium-wage firms, and null effects for high-wage firms. On the other hand, I find that growth in world import demand at the firm leads to higher employment.

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 additional exercises, however, suggest that the causality runs through CB units. First, I find robust estimates to varying controls for connections via local labor markets, suggesting that the effects are not driven by spillovers through proximity. Second, I find that CB shocks also affect non-exporting firms in the same CB unit, suggesting that exporter-specific unobservables are not responsible for the results. Finally, I construct a falsification test that focuses on a subset of firms covered by more than one CB unit, and estimate 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 CB unit-specific effects within the firm. I find that workers' wages respond to shocks to their own CB unit within the firm, which strongly suggests that the effects are driven by CB.

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, defined by region and economic sector, which are affected by wage floors. CB units, defined as partitions of local labor markets, bargain over a common wage floor anticipating the response of covered local markets. 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 export shocks in the model, and verify that it is able to replicate the qualitative empirical patterns in the data.

The model allows me to assess the role of the CB network in the propagation of shocks. I define counterfactual networks that vary in the size of CB units, a proxy for the degree of centralization of bargaining, and simulate the effects of the export shocks. Decentralized bargaining countries include the US and the UK, while France and Italy are examples of more centralized networks (Bhuller et al. 2022). The model yields two main results. First, wage floors are more responsive to shocks when the CB unit is more homogeneous in terms of productivity. Because wage floors are common to all firms in the CB unit, unions will not respond as much to positive shocks in high productivity regions as they could harm low productivity regions. Second, more centralized bargaining does not always result in more shock propagation. Decentralized bargaining results in high responsiveness of local wages to shocks, but trivially does not propagate shocks across local labor markets. On the other hand, as unions want to prevent employment costs associated with high wage floors in low productivity local markets, networks with highly centralized bargaining endogenously result in less binding wage floors. Consequently, CB networks with intermediate levels of centralization result in more shock propagation. This result suggests that the degree of risk sharing of shocks between firms is higher in networks where CB units are of moderate size.

This article contributes to several strands of literature. First, to my knowledge this is the first paper to show direct evidence that the wages paid by a given firm are affected by shocks to other firms in the same CB unit. Rose (1987) and Abowd and Lemieux (1993) find wage responses to shocks to CB units in different contexts.[5] Gürtzgen (2009b) and Rusinek and Rycx (2013) find that wages are more responsive to firm shocks when bargaining is decentralized. None of these papers distinguish between the effects of shocks to a firm and to other firms in the same CB unit, nor do they explore the response of firms according to their productivity. Additionally, my result of larger wage responses to CB shocks than to firm shocks suggest that the different magnitudes of rent-sharing elasticities in the literature may be explained by the level at which wages are negotiated. For example, findings in Abowd and Lemieux (1993) using contract wages from CB agreements suggest an elasticity of 0.2, twice as high as the average elasticity of 0.1 across worker-level specifications reported by 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). 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. Giroud and Mueller (2019) find that shocks propagate spatially through firms' internal networks. Borusyak et al. (2022a) notes that the effects

[5] Rose (1987) studies the response of wages in a deregulation episode in the US trucking industry. Abowd and Lemieux (1993) study the response of contract wages to changes in international prices in Canadian manufacturing.

of regional shocks on migration depend on a region's shock and on the shocks of other regions as well. None of these papers discuss the role of bargaining institutions, nor do they study how alternative CB networks affect the propagation of shocks.

Additionally, 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. While prior work exists modelling bargaining institutions in different settings, it usually does not feature firm heterogeneity or spatial linkages.[6] In principle, the model can be used to study other questions in a spatial setting for which bargaining may be important, such as the connection between collective bargaining and regional inequality.

Finally, the paper contributes to a broad literature studying unions and collective bargaining (e.g., Freeman and Medoff 1984; Card 1990, 1996; Moene et al. 1993). In particular, several papers have studied the properties of different bargaining regimes both theoretically and empirically (e.g., 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 stylized 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 with heterogeneous firms covered by a single CB unit. The goal is to determine the likely response of wages, wage floors, and employment to shocks, and to derive testable predictions for the empirical analysis discussed in Section 4. While this section presents a stylized discussion of partial equilibrium effects under a single CB unit, the model of Section 6 will allow for multiple CB units and for general equilibrium effects.

2.1 Firm heterogeneity and wage floors

Firms j face an upward-sloping labor supply curve $\ell_j(w_j)$ at wage w_j. In Section 6, ℓ_j will also depend on a measure of aggregate wages, capturing general equilibrium effects. Firms are heterogeneous in productivity φ_j, and the production function is $y_j = \varphi_j f(\ell_j)$. For simplicity,

[6] Several articles present theoretical models to study the role of bargaining. For example, Calmfors and Driffill (1988) study the relationship between centralized bargaining and the level of unemployment, and Corneo (1995) and Naylor (1998) study how the bargaining structure affects the response of national labor markets to trade integration.

the output price is normalized to 1. A wage floor $\underline{w}$ sets a minimum to the wage that firms can pay. The firm's static decision problem is thus given by

$$\max_{w_j} \varphi_j f(\ell_j(w_j)) - w_j \ell_j(w_j) \quad \text{s.t.} \quad w_j \geq \underline{w}.$$

The solution is characterized by two thresholds that determine firms' behavior given their productivity (Ahlfeldt et al. 2022), which I denote by $\underline{\varphi}$ and $\overline{\varphi}$. Firms with $\varphi_j > \overline{\varphi}$ are *unconstrained* by the wage floor. They optimally choose wages above the floor, so 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). The model implies that these firms will not be affected by marginal changes in the wage floor.

Firms with $\varphi_j \leq \overline{\varphi}$ are *constrained* by the wage floor, so that $w_j^* = \underline{w}$ and $\ell_j^* = \ell_j(\underline{w}, \varphi_j)$ for them. When $\varphi_j \leq \underline{\varphi}$ as well we have that $d\ell_j(\underline{w}, \varphi_j)/d\underline{w} < 0$, i.e., these firms lower employment when $\underline{w}$ increases. They do so because, at their monopsony equilibrium, the marginal revenue product of labor (MPL) equates the marginal cost of labor (MCL) at a level lower than $\underline{w}$. Thus, as the MCL increases to $\underline{w}$, these firms need to increase the MPL to equate it to $\underline{w}$, 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 the wage floor causes them to increase employment. At their monopsony equilibrium, the equality between the MPL and the MCL is achieved at a level higher than $\underline{w}$. When the MCL decreases to $\underline{w}$, these firms want to lower the MPL, which they do by increasing employment. By reducing monopsony power, the wage floor increases employment for this group of firms.

2.2 Nash bargaining and the effects of shocks

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 $WB(\underline{w}) = \sum_{j\in\mathcal{J}} w_j \ell_j$, where $\mathcal{J}$ is the set of firms in the CB unit. I assume that the objective of the union is to maximize the wage bill $U(\underline{w}) = WB_c(\underline{w})$, and that the objective of the employers is to maximize aggregate profits $\Pi(\underline{w}) = R(\underline{w}) - WB(\underline{w})$. Allowing for more structure in Section 6, I will show that the wage bill is hump-shaped in the wage floor, and that the profit function is decreasing in the wage floor. We assume that, in case of a floor $\underline{w}'$ that is not binding, aggregate profits are positive ($R(\underline{w}') > WB(\underline{w}')$). Letting $\beta \in [0, 1]$ be the bargaining power of the union, the Nash bargaining problem is

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

If $\beta = 1$ the problem amounts to selecting the wage bill-maximizing wage floor, whereas if $\beta = 0$ the problem amounts to selecting the profit-maximizing wage floor (which will be non-binding).

Now consider the case $\beta \in (0,1)$. The optimal wage floor is implicitly defined by

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

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

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

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 allow for an outside option for workers in the objective function U, then we would get the familiar result that average wages are a weighted average of revenue per worker and the outside option. The solution is thus analogous to the classical Nash bargaining problem in which unions set wages instead of wage floors. The main difference is 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 to shocks)**.** *Assume a change in the productivity profile $\{d\ln\varphi_j\}$. Holding ω fixed, the resulting change in the wage floor is*

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

where $s_j^R = R_j/R_c$ is the share of revenue of firm j in the CB unit and $s_j^{WB} = WB_j/WB_c$ is the analogous wage bill share, $\tilde{WB}_c^{\text{co}}$ 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 that depends on the responses of the ratio $(-d\Pi/d\underline{w})/(dU/d\underline{w})$ to the changes in productivity and the wage floor.

Proofs are available in Appendix A. Proposition 1 shows that, holding ω fixed, $\underline{w}$ responds to a weighted average of changes in log productivity minus a weighted average of wage bill elasticities times changes in log productivity. The adjustment term reflects the fact that firms respond to the 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, then $\underline{w}$ needs to rise by less to restore equilibrium. If ω is allowed to vary then the response of $\underline{w}$ will also depend on a term that reflects the changes in the ratio $(-d\Pi/d\underline{w})/(dU/d\underline{w})$.

We also note that the response of $\underline{w}$ is decreasing in the adjusted constrained wage bill $\tilde{WB}_c^{\text{co}}$. As $\tilde{WB}_c^{\text{co}}$ is decreasing in β, stronger unions will result in a more responsive wage floors.[7]

Proposition 2 (Response of wages and employment to shocks)**.** *Assume a change in the productivity profile $\{d\ln\varphi_j\}$ that leads to the wage floor change given by (4).*

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

1. *For unconstrained firms we have that* $d \ln w_j = (dw_j(\varphi_j)/d\varphi_j)\,\varphi_j d\ln\varphi_j$ *and that* $d\ln\ell_j = (d\ell_j(w_j)/dw_j)\,w_j d\ln w_j$*. Wages and employment respond positively to productivity shocks.*
2. *For constrained firms we have that* $d\ln w_j = d\ln \underline{w}$ *and that* $d\ln\ell_j = (\partial\ell_j(\underline{w},\varphi_j)/\partial w)\,\underline{w} d\ln\underline{w}$*. Wages respond in the same direction as the wage floor. The direction of the employment response depends on* $\partial\ell_j(\underline{w},\varphi_j)/\partial w$*, which sign depends on the relationship between* φ_j *and the thresholds* $\underline{\varphi}$ *and* $\overline{\varphi}$*.*

Proposition 2 establishes the response of wages and employment to the entire profile of shocks. The model implies that unconstrained firms should only be affected by their own shock.[8] For constrained firms, a corollary of Proposition 2 is that productivity shocks that increase average CB revenue will unequivocally lead to higher wages. However, the effect of shocks on average employment is heterogeneous, and depends on the baseline level of firm productivity. I will use this prediction in the empirical analysis to test whether the responses to shocks that affect firms via CB can be rationalized by changes in the wage floor.

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 the analysis 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.

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, implying that the CB network has been stable in the study period. A union with bargaining privileges can sign two types of agreements. A "master CBA" is a comprehensive contract that sets standards for all workers in the area, and defines the CB units.[9] "CBA alterations" act as amendments to master CBAs, are

[8] Unconstrained firms may also be affected by the wage floor if spillover effects are present. For example, Cengiz et al. (2019) in the US and Milgrom and Verdugo (2022) in Chile find evidence of spillovers from minimum wage policies. Bassier (2022) finds spillover effects across firms in South African collective bargaining.

[9] A master CBA may be modified by a new master CBA that supersedes it, or a CBA alteration that updates some provisions in it. Expired master CBAs remain in force until renegotiated due to a clause known as "ultra-activity," a feature common to many countries.

signed more frequently, and typically refer to updates in wage scales. Usually, national master CBAs allow for variation in wage floors across regions (most typically for the southern provinces), although this variation is usually constant over time. Additionally, the law allows a single employer to hire 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, which defines its CB unit, although I use firms that have workers in multiple CBAs for a falsification exercise.

The definition of the coverage of master CBAs, which follows from the union's area of representation, is based on verbal descriptions and is not exact. As an example, Table 1 shows the description from three textile-related master CBAs. It is not possible to tell from the descriptions what CBA will cover a firm that declares as economic activity some subgroup of textile manufacturing, such as "weaving of textiles" or "manufacture of wearing apparel." For instance, CBA 0500/07 covers "workers in the textile industry" and 0501/07 covers "workers ... from clothing industrial companies and related fields." This results in an idiosyncratic CB network in which firms that in the same economic activity and province operate under different CB units.

Coverage of CB is nearly universal, with exceptions only for managerial roles and certain professions. 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 the labor market institutions in Argentina.

3.2 The socio-economic context

Figure 1 shows the trajectory of the Argentine economy in the years 2004–2019. Panel (a) shows the evolution of GDP and Panel (b) the inflation rate. 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, growth continued for a few more years though with increasing inflation rates. However, the economy started to slow down, and by 2015 real GDP had been stagnated for 4 years and annual inflation had risen above 30%. Despite a change in the ruling party in December 2015, the economy continued to stagnate and even fell into the COVID pandemic.

The figure also illustrates two important features of the Argentine economy that are relevant for the analysis. Panel (c) shows the evolution of exports per broad category. We observe a large increase in exports following the Great Recession. In the next section we will see that this increase was partly driven by a persistent surge in international demand for Argentine products. I will leverage heterogeneity of this demand increase across destination countries and detailed products to construct my identification strategy. Panel (d) shows a strong increase in the frequency of CBA alterations from 2005 to 2010, which responds to the increase in inflation rates. 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

I use two administrative registries to obtain information on labor market outcomes for private sector workers. The first one I 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 do not include information on hours or full-time status, so I use the main hiring modality to proxy for it. Second, I use data from *Simplificación Registral*, a national system introduced in 2008. The dataset contains information at worker hiring and termination dates, and includes the (master) 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.

I use two additional data sources. First, to construct export shocks I rely on international trade flows data from BACI-CEPII (Gaulier and Zignago 2010) for 2007–2020, and administrative data from Argentine Customs for 2011–2020. 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.

Due to the gradual implementation of *Simplificación Registral* the CBA code has missing values. I take several steps to impute this variable, increasing coverage from 70% to 85% after 2011. The most important step involves imputing the CBA code to workers with missing values in a firm that only declares a single CBA. I also harmonized CBA codes so that they represent a constant CB unit. Upon cleaning the worker-level CBA code, I designate a "primary CBA" to each firm, which designates its CB unit. All firms in the economy are assigned a CB unit.

Appendix B.2.1 provides more details on the data.

Heterogeneity in CB coverage. I use a firm's CB unit to explore the structure of the CB network. The median CB unit spans across 3 provinces and 4 economic sectors (4-digit). The 25th and 75th percentiles are 1 and 8 provinces, and 2 and 11 sectors. The most prevalent CB unit, which covers workers in wholesale and retail trade, is present in all 24 provinces and 262 out of 295 sectors. There are many cases of multiple CB units within the same sector and province.

Appendix Figure 1 shows the distribution of the Herfindahl-Hirschman Index (HHI) of the number of firms across different CB units within 4-digit sector and province cells. An exact alignment between CB units and sector-province cells would result in an HHI of 1 for all cells. However, we observe a large dispersion of HHIs. 40% of cells have an HHI lower than 0.5, equivalent to 2 equal-sized CB units in the cell. Appendix Figure 2 further illustrates this heterogeneity using textile-related sectors. It is easy to see that the three main CB units, whose descriptions of the coverage of workers are shown in Table 1, appear in all three sectors.

[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.

Estimating wage floors. The administrative data provides a CBA code and a code for the worker's occupation category within the CBA. Unfortunately, it does not directly include wage floors.[11] I estimate wage floors by detecting bunching in the distribution of wages within CBAs, categories, CBA-regions, and month cells. Then, I smooth the wage floors using time and cross-sectional variation so that the percent difference across categories is constant and all categories experience the same growth over time, reflecting the usual structure of within-CBA wage floors in the agreements. I also drop cells for which variation in the estimated wage floors is implausible. For validation, I compare the estimated wage floors with a sample of manually collected wage floors. Appendix C discusses the details of this procedure.

The estimated wage floors do a great job at replicating the levels of the manually collected wage floors. However, the wage floors collected manually exhibit, on average, somewhat larger changes in semester averages. A potential explanation for this divergence is that the manual collection potentially missed some nominal wage floor increases, or some time-varying component of the base pay of workers, that is captured in the estimated wage floors. Overall, I conclude that wage floors align well among data sources. Additionally, there is no reason to suspect that measurement error in the estimated wage floors would be correlated with the export shocks.

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. I compute the average monthly real wage and wage floor for each firm-year, deflating monthly wages by the consumer price index. I also tally the number of workers that appear in the year, and compute the share of workers in the main hiring modality (which proxies 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 export 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 granular products to construct firm and CB unit 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 Overview

This paper aims to uncover the causal effect of a shock to the firm's product demand and to the product demand of a firm's peers in the CB unit. An ideal experiment to identify these

[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.

effects would consist of randomly changing the demand for different granular products to generate exogenous variation in the demand for each firm. The effect of a product-demand change at the firm could be estimated by comparing firms with different changes, conditional on the changes to the firm's peers. As bargaining outcomes are defined by the average product-demand change across firms in the CB unit—as discussed in Section 2—, the average of the firm-level product demand changes across CB units should have variation as well. Then, conditioning on the product demand change to a firm, the effect of a shock to the firm's peers in the CB unit could be estimated comparing firms across CB units. As yearly negotiations unfold over time and incorporate changes in the profitability 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 experiment I construct shocks to firm and CB units using variation arising from changes in world import demand for granular products exported by Argentine firms, and rely on a difference-in-differences strategy to estimate their effects. I describe this strategy, and discuss identification assumptions and falsification exercises, in the remainder of this section.

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 unit 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. Similarly, for each CB unit c, I define the shock as

$$z_c = \sum_{j\in\mathcal{J}} s_{cj} z_j = \sum_{j\in\mathcal{J}} s_{cj}\left(\sum_{p\in\mathcal{P}} s_{jp} f_p\right) = \sum_{p\in\mathcal{P}} s_{cp} f_p.$$

where $s_{cj} = L^{EX}_{cj}/\left(\sum_{j'\in\mathcal{J}} L^{EX}_{cj'}\right)$ is the share of workers in exporting firm j in CB unit c, and $s_{cp} = \sum_j s_{cj} s_{jp}$ denotes the contribution of p to c's shock. 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, which should be affected by the CB shock z_c. Shocks are not defined for CB units without exporting firms, which are excluded from the empirical analysis. Appendix Figure 3 shows the distribution of both z_j and z_c. The distribution of the firm shock is bell-shaped around a positive mean. In comparison, we observe slightly more variation in the CB shocks, suggesting that some CB units 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 evolution of the average shock 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. 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 plausibility of this interpretation in the next subsection.

4.3 A difference-in-differences strategy

Let $I\{\cdot\}$ be an indicator function. The 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 $\delta_{\ell(j)t}$ are ℓ-specific year fixed effects, 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 sample of firms observed in a survey of businesses 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. Appendix Figure 4 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 local labor market fixed effects. 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.

[12] The raw correlation is slightly stronger when I focus on larger firms. This is to be expected given the definition

Throughout the paper, I cluster standard errors at the CB unit level.

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 my case country-product categories—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 develops the identification argument from Borusyak et al. (2022b) in my setting, and extends it to a scenario with two shift-share variables. The key assumption is that changes in world import demand for each country-product p are mean independent of average residuals of firms that export in that country-product both when weighted by the exposure shares via firms and by exposure shares via CB units. This assumption would be violated if, for example, firms that export a particular product that experiences an increase in demand 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? Appendix Figure 5 shows estimates of a regression at the firm level of the firm shock pre-period firm characteristics (from the period 2007–2009) and the CB shock. 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 6 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 5 shows that the correlation of the firm shock with the pre-period firm shock and firm size become insignificant after dropping these firms and adding controls.

Systematic correlations of CB shocks with observables at the CB unit level would be concerning as well. Appendix Figure 7 shows that the CB shocks are not correlated with the pre-period CB shock, the number of firms in the CB unit, and the share of employment in exporting firms.

The assumption that shocks are quasi-randomly assigned implies that the shocks should not affect outcomes before they occur. I explore whether this holds by means of pre-trends testing, comparing outcomes for firms that received similar shocks prior to their occurrence.

Baseline sample. I define my "baseline sample" out of the sample of exporters as follows. I keep firms that were operational in 2007 through 2009, had an average of 1 to 500 workers in

of shocks to CB units.

[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.

[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 export shocks.

the same period, and exported between the 1st and 99th percentiles in 2011–2012.[15] I do so to make sure that outliers do not drive the results. To reflect the fact that there is stronger mean reversion at the left tail of the firm shock, 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 discuss the robustness of the results to these restrictions.

Appendix Table 1 shows cross-sectional statistics of the baseline sample of firms. 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 2 shows cross-sectional statistics of the 152 CB units that cover these firms. The average CB unit has 50 exporting firms. Lastly, Appendix Table 3 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 CB units, and a second one at the worker level for workers observed continuously in exporting firms.

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 CB units 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.

Falsification, robustness, and heterogeneity. I conduct several additional exercises to, first, test for potential threats to the empirical strategy and explore the robustness of the results, and second, to study heterogeneity in the effects of shocks and explore whether changes in the wage floors are responsible for the effects of CB shocks. I explain these exercises in more detail in the next section.

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 wage floors. I discuss the magnitude of effects using complementary estimates of the effect of the firm shock on revenue. Second, I explore the effect of shocks on employment, and use heterogeneity analysis to study whether responses to CB 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 country-product (they have "incomplete shares"). I drop these firms from the analysis, which after accounting for other restrictions results in only 1 extra firm dropped in the baseline sample.

can be rationalized by a wage floor mechanism. Third, I compare my estimates with the literature. Finally, I present a set of falsification tests and robustness checks.

5.1 Effects on wages and wage floors

Figure 3 shows the average evolution of wages by level of the CB shock and firm shock, relative to 2009. We observe that CB units with larger shocks consistently experience larger increases in wages. On the other hand, there seems to be a small increase in wages, if any, following a firm shock. 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.

Figure 4 shows estimates of the dynamic model on mean wages and wage floors, controlling for time-varying local labor market fixed effects and firm characteristics. Panel (a) shows 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) shows estimates of the same model but using the log mean 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. We observe a strong increase in wage floors following a CB shock, of a similar magnitude as the increase in wages, and a precisely estimated null effect of the firm shock. This is reassuring as firm shocks are not supposed to affect wage floors.

Table 2 shows estimates of the static model. Column (1) shows that wages increase by 0.0482% in response to a 1% rise in average world import demand in the CB unit, and by 0.0173% following a 1% rise in average world import demand in the firm. While the coefficient on the CB shock is strongly significant ($t = 2.64$), the coefficient on the firm shock is only marginally so ($t = 1.48$). Column (2) of Table 2 shows an effect of the CB shock on log mean wage floors of 0.0505 ($t = 2.57$). Column (3) of Table 2 shows the effect of the CB shock on the "wage cushion" (the log ratio between the wage and wage floor), which is indistinguishable from zero.

A natural question is whether the effects of shocks differ across CB units. Figure 5 replicates the static model but interacting the CB shock with an indicator for the size of the CB unit. The effect of the CB shock on wages and wage floors is driven by larger CB units, suggesting that larger CB units may have stronger bargaining power and thus be more effective at raising wages. Appendix Figure 8 replicates the dynamic model but excluding firms covered by the retail CB unit 0130/75, arguably the most binding in the economy.[16] In this case we observe a stronger effect of a firm shock on mean wages, as can be seen in Panel (a). The average effect of the firm shock is 0.0285, ($t = 2.76$). The effect of the CB shock on wages is similar as in the baseline. This result suggests that wage-setting institutions matter also for the effect of firm shocks on wages.

The magnitude of effects. To better interpret the magnitude of these effects, I scale them by the effect of the firm shock on revenue. Figure 6 shows effects of the firm shock on product-market sales and labor expenditures labor using data from a survey of businesses, which is available for

[16]This restriction reduces the number of firms in the sample by 28.2%.

2010–2016 (excluding 2013). Because these years 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 following the shock. A 10% increase in average world import demand rises product-market sales by 1.13%, and labor costs by 0.87%, on average in relative years 1–3.

Following these results, assume that a 10% change in z_j translates into a 1.1% increase in firm revenue. Then, a 10% CB shock can be interpreted as a 1.1% increase in firm revenue for all firms in the CB unit. Using the results in Table 2, this implies that a 10% increase in revenue of all firms in the CB unit increases wages by $10 \times (0.048/0.11) \approx 4.3\%$. Similarly, a 1% increase in firm revenue increases wages by $10 \times (0.017/0.11) \approx 1.5\%$ and employment by $10 \times (0.024/0.11) \approx 3.5\%$. Using the estimates for the firm shocks that exclude the retail CB unit, we would conclude that a 1% increase in firm revenue increases wages by $100 \times (0.025/0.11) \approx 2.3\%$.

5.2 Effects on employment

Appendix Figure 9 shows the evolution of employment by level of the CB shock and firm shock, relative to 2009. We observe lower employment growth in firms that experienced a low CB shock, and stronger growth in firms with a high firm shock. However, in this case the patterns are less clear than for the evolution of wages shown in Figure 3.

Figure 7 shows estimates of the dynamic model using log employment as outcome. We observe a noisy response of employment to the CB shock that is statistically indistinguishable from zero. The theory discussed in Section 2 suggests that this is to be expected, as firms with different productivity levels will systematically respond differently to the CB shock. On the other hand, we observe a strong increase in employment following a firm shock, which is statistically significant. Table 2 shows estimates of the static DiD model. 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 ($t = 2.21$). 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 8 replicates the dynamic model but excluding firms covered by the retail CB unit 0130/75, arguably the most binding in the economy. As noted before, Panel (a) shows a stronger effect of the firm shock on wages in this sample. We also note a smaller effect of the firm shock on employment, which is not statistically significant. This figure suggests that firms outside the retail CB unit responded to the firm shock by increasing wages rather than employment.

5.3 Heterogeneous responses to CB shocks

A threat to the interpretation that CB 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, a positive CB shock that affects wage floors should cause low-productivity firms, which are constrained by the wage floor, to decrease 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 CB unit by province cell, excluding cells that have fewer than 8 firms. 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.

Figure 8 displays the coefficients of the heterogeneity analysis. Panel (a) shows that firms in the lowest quartile of pre-period wages respond to the CB shock by decreasing employment. The figure also shows a decline in the share of workers in the main hiring modality for these firms, indicating that full-time workers are more likely to separate. There are also positive employment effects for firms in the third quartile, and non-significant effects for firms in the second and fourth quartiles. These patterns are consistent with low-wage firms moving along the supply curve, and with the presence of monopsony power in the labor market. 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 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 seems lower than in the second quartile due to the employment response, as high-wage workers are the ones separating from firms in the first quartile.

Appendix Table 4 provides detailed regression results. The hypothesis of equality of employment responses between the first and second, and first and third quartiles can be confidently rejected at the 5% significance level. The hypothesis of equality between the first and fourth quartiles cannot be rejected. For the share of workers in the main hiring modality the hypothesis of equality between the first and any quartile can be confidently rejected. These patterns are consistent with bargaining propagating the effects of CB shocks through wage floors.

5.4 Comparison with the literature

The most methodologically related paper is Garin and Silvério (2023). Using a similar shift-share strategy in Portugal, the authors find that an "idiosyncratic" export 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.

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 0.099, which is again comparable with my firm-level estimates. The authors also find that industry-level specifications, and calibrations of bargaining power in macro models, tend to find larger estimates. For example, Abowd and Lemieux (1993) use contract wages from CB agreements and shocks to international prices in Canadian manufacturing. Their estimates suggest an elasticity of 0.2, twice as high as the average elasticity of 0.1 from worker-level specifications.[17] I find that the response to a change in average product-demand at the CB unit is almost 3 times larger than the response to a change in product-demand at the firm. This result suggests that using shocks aggregated at the level at which wages are negotiated can affect the magnitude of rent-sharing elasticities.

5.5 Falsification tests and robustness checks

In this subsection I present additional empirical exercises to assess the robustness and validity of the empirical results.

Firms with multiple collective bargaining agreements. A minority of firms declare workers under more than one CB unit, thus making an interesting case study to assess whether what matters is the CB unit 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 CB unit propagate through other channels, we should not observe CB-specific effects within the firm. However, if the shock propagates through the worker's CB unit, we should observe an effect on wages of workers declared under that CB unit.

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. Figure 9 shows the estimates. Panel (a) replicates the baseline results: a positive shock to the primary CB unit in the firm increases wages. This specification controls for worker by firm ("match") effects. Panel (b) estimates a model that uses the CB shock of the worker's CBA, instead of the primary CB unit 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 6 provides detailed regression results from the worker-level analysis using static models. Columns (1) through (3) show consistent positive effects of CB shocks to the primary CB unit of the firm when varying local labor market controls, with column (3) corresponding to the specification in Panel (a) of Figure 9. Column (4) shows that the effect of the primary CB shock on wages is driven by workers that are actually declared under the primary CB unit. The effect on wages of workers declared under a CB unit different from the firm's primary one is smaller in magnitude and not statistically significant. Finally, Column (5) replicates the model in Panel (b) of Figure 9.

Controls for local-labor-market effects. A key concern is that the results may be driven by spillovers between firms through proximity instead of the CB network. I explore this possibility in

[17] Card and Cardoso (2022), who does not rely on quasi-experimental variation, find that wage floors respond to changes in average value-added per worker with an elasticity of around 0.1.

Appendix Table 5, where I show estimates that use 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 export shock computed similarly to the CB shock but at the 6-digit sector level. The results are similar across specifications, suggesting that spillovers through proximity are not responsible for the results.

Effects on non-exporters. So far, I have focused on exporting firms, but CB shocks should affect non-exporting firms as well. To test for this, in Appendix Figure 10 I estimate the effect of CB shocks on wages and the wage floor using all firms covered by the CB unit. I 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.

Placebo CB units. 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 CB unit code across firms within each 1-digit sector and province. Appendix Figure 11 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. A final concern is that regression controls or sample restrictions may be driving the results. Appendix Table 7 varies the set of controls included in the regression, and shows very similar results when dropping the firm-level controls, controlling for the pre-period firm shock directly, and excluding the control for the pre-period CB shock. Appendix Figure 12 replicates the dynamic estimates on wages and employment keeping firms with extreme values of the pre-period firm shock, relaxing one of the sample restrictions. 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, as discussed in the previous section, I find the exclusion of these firms to be justified, it is important to note how the results change when they are included.

Appendix Table 8 varies 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 to 0.0320, although the coefficient is still significant at the 10% level ($t = 1.91$). Column (3) shows that dropping CB units with more than 100 firms in the sample seems to increase this effect. Consistent with Figure 5, larger CB units seem to respond more strongly to CB shocks. Column (4) shows results of the static model when excluding the retail CB unit, i.e., the analogous specification to Appendix Figure 8 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, and a CB network. The model is later estimated and used to analyze the role of the CB network in shaping the effects of shocks on the labor market.

6.1 Set-up

There is a fixed population of N_r in each region $r \in \mathcal{R}$, each with separate labor markets. Regions are divided in local labor markets $g \in \mathcal{G}$, which are also characterized by an economic sector $k \in \mathcal{K}$. I denote by $\mathcal{K}1$ the 1-digit groupings of sectors. A given sector and region cell may be partitioned into multiple local markets. Each local market contains a continuum of firms, indexed by j, and the measure of firms 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 markets in the unit.[18]

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 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 g decide employment and wages under monopsonistic competition, and wage indexes adjust to clear the regional labor markets. 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 changes in productivity distributions of local labor markets.

6.2 Solving the model

I solve the model backwards starting with the worker and firm's problems, and then moving into the bargaining game between CB units.

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

[18] I allow for regional differences in wage floors within CB units. Following common practice in Argentina, I assume that they are constant and do not respond to shocks.

choice models. Then, it can be shown that labor supply to a firm located in 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 r, V_r, is proportional to the regional wage index. Let $\Gamma(\cdot)$ denote the gamma function, then

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

Before choosing a firm, workers decide whether to work formally or not. Workers' preferences 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:[19]

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

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

[19] I assume a linear technology for analytical convenience. The main results will be qualitatively similar under alternative specifications.

they experience negative profits $\pi(\underline{\varphi}) < 0$, implying thresholds

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

Consistent with Section 2, employment may decline following wage floor increases when firms with $\varphi < \underline{\varphi}$ exit the market. If $\underline{w}_c < \mu\varphi_{g0}$, then 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 $\alpha > 1$ whose 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 $x > \varphi_{g0}$, given by $F_g(\varphi|x) = 1-(x/\varphi)^{\alpha}$. 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).

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, the share varies between 0 and this maximum value. Appendix Figure 13 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 productivities. The minimum value of this integration might be φ_{g0}, $\underline{\varphi}_g$, or $\overline{\varphi}_g$ depending on the value of $\underline{w}_{c(g)}$. To compute aggregate labor demand I integrate over the distribution of "possible" firms in g, so the minimum value will always be φ_{g0}. Formally, $L_g = M_g \int_{\varphi_{g0}}^{\infty} \ell(\varphi) f_g(\varphi) d\varphi$, where $f_g(\varphi)$ is the pdf of the Pareto distribution. This is the relevant quantity to determine the bargaining equilibrium, as the measure of firms in the market would then respond to the wage floor. Appendix F.1 shows expressions for several aggregate quantities at the local labor market level, such as revenue and the wage bill.

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 the objective function of the union is given by $U_c\left(\underline{w}_c, \underline{\mathbf{w}}_{-c}\right) = \sum_g WB_g$, where WB_g is the wage bill in g, and the objective of the employer is $\Pi_c\left(\underline{w}_c, \underline{\mathbf{w}}_{-c}\right) = \sum_g (R_g - WB_g)$, where R_g is revenue in g. 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.

In this formulation, the union is concerned with maximizing total wages, instead of worker welfare. In Argentina, unions receive a fee proportional to each payslip, so this is equivalent unions trying to maximize their revenue.[20]

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.[21] 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.[22] In the setting of this model, $\{\underline{w}_c^*\}_{c\in\mathcal{C}}$ is a Nash-in-Nash solution if

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

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 $\{\mu_r^*\}_{r\in\mathcal{R}}$

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

[21] Davidson (1988) studies a two-union bargaining game and uses a similar solution concept.

[22] This assumption is debatable if a single union takes part in multiple CB units. While I assume separate unions across CB units, Collard-Wexler et al. (2019) show that the Nash-in-nash solution can be micro-founded in a fully non-cooperative environment where players internalize the interdependence of their potentially multiple bargains.

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.

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

Starting from the firm-level data I construct a dataset at the local labor market level. I specify sectors $k \in \mathcal{K}$ as a coarsening of the 4-digit sectors, and regions $r \in \mathcal{R}$ as a grouping of provinces in Centro (center, including Buenos Aires), Cuyo (west), Norte (north), and Patagonia (south), and I drop the 1-digit sectors associated with agricultural production, education and government.[23] I further divide the economic sector by region cells using the observed CB network and the exporting status of firms. I use several criteria to avoid having small cells, constructing "local CB units" that cluster together firms that are in small cells. For instance, if a cell has less than 5 firms, I assign it to the local CB unit category. Appendix F.3 provides details.

I aggregate the firm-level data to the local labor market level. To estimate wage floors I compute the mean of the firm-level average wage floor across workers, weighting by the share of workers with an assigned wage floor. I allow regional wage floors within a CB unit only if the region's average wage floor is sufficiently different from the rest. To estimate the share of firms constrained by the wage floor I use the workers that were assigned a wage floor. 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.

Appendix Table 12 provides summary statistics. There are $1,018$ CB units, of which 696 are local. 61.4% of local labor markets are in the region "Centro," 17.9% are covered by a local CB unit, and 21.2% are covered by the retail CBA. We observe a few small local labor markets where the mean wage is lower than the wage floor. This is likely due to the fact that small local labor markets rely strongly on part-time work, so those workers earn less than the wage floor. I account

[23] I drop these sectors because bargaining is regulated by different regimes. Additionally, the agricultural sector represents a small share of employment.

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 9 and detailed in this section. Appendix F.4 provides details.

Worker problem. To estimate the preference heterogeneity parameter η and the amenity values $\{A_{k1}\}_{k1\in\mathcal{K}1}$, I leverage the relationship between firm size and firm wages implied by the labor supply to the firm (6). In particular, I estimate a regression of log mean wage on log firm size, controlling for region and 1-digit sector fixed effects. While the model implies an exact fit of this regression, it is straightforward to incorporate hours to allow for an error term, as discussed in the appendix. I find a value of $\eta \approx 4.10$, which is in line with the literature. This value implies a markdown factor 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 productivities $\{\varphi_{g0}\}_{g\in\mathcal{G}}$, I invert the 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 12 shows summary statistics of the estimated minimum productivities. The values are measured in Argentine pesos, and are on average larger than the minimum wage, which per (11) is the lower threshold that defines whether firms exit the market.

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 interior equilibrium. 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 14.

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 so large that it has significant general equilibrium effects. 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 14 shows the estimated bargaining power parameters. We observe a great deal of heterogeneity. Appendix Figure 15 shows the correlation between the estimated bargaining power parameters and CBA-level observables. Panel (a) suggests a weakly positive correlation with total employment in the CB unit. Panel (b) shows a positive correlation with the average outside option in the CB unit 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 cannot be accounted for by CB characteristics.

7.3 Validation

I validate the model comparing data moments with model-based predictions. To do so, I use the minimum productivities, and other parameters estimated above, to compute the model-implied version of mean wages in each local labor market in 2011–2012. First, I compare the correlation between mean wages and wage floors in the data and the model. Panel (a) of Figure 10 shows that the model does a good job at replicating the correlation between mean wages and wage floors, with log mean wages being almost a parallel shift of log wage floors. Unsurprisingly, as production technology is very simple in the model, the data show more variation in average wages than the model. Appendix Figure 16 shows that the model also does a good job at replicating the correlation between the share of firms bunching at the wage floor and the mean wage.

Second, I compare mean wages in the data and the model. Importantly, mean wages in the data were not used in estimation and, as shown in Appendix Figure 16, they are very weakly correlated with the share of firms bunching at the wage floor, which is the key input to estimate the minimum productivities. Panel (b) of Figure 10 shows that the observations cluster around the 45 degree line, indicating that the model does a good job at replicating the mean wage in each local labor market. Once again, we note more variability of wages in the data.

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 so, I first estimate the effect of trade shocks on aggregate revenue using data from the survey of businesses. Appendix Table 13 shows that aggregate revenue increases by about 22% in exporting local labor markets, and this conclusion is similar when 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 DiD strategy.

Appendix Table 14 estimates the effects of CB shocks on log wages and log wage floors, in the aggregate data and the model-generated data. The results are noisier than in the firm-level estimates, 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, which Panel (b) of Figure 8 suggests are important.

Overall, the model does a good job at capturing the main features of the data. Next, I use the model to explore the propagation of shocks under different bargaining networks.

8 Model-Based Counterfactuals

In this section, I use the estimated model to explore how shocks propagate through the labor market under different bargaining networks. First, I define the counterfactual bargaining networks used in this section. Second, I illustrate how shocks propagate through the labor market under different bargaining networks. Third, I explore how the degree of centralization of bargaining affects the propagation of shocks. Finally, I discuss the implications of the findings.

8.1 Counterfactual networks

I construct counterfactual CB networks as follows. First, I simplify the baseline network 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 parameters of observed CB units, weighting by the measure of local labor market size M_g.

These networks differ in the degree of centralization of bargaining or, in terms of the classification in Bhuller et al. (2022), 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 in a sector

Figure 11 shows how shocks propagate to wages for different CB networks, using as example local labor markets in the economic sectors that manufacture pesticides, and soaps and detergents. The figure is composed of several graphs with nodes, each of which represents one local labor market. Importantly, not all local labor markets in the CB units in the graphs are shown. Panel (a) shows the change in revenue for each local labor market following the export shock. We note variation in the magnitude of the shock across these markets. Panel (b) and Panel (c) show how the shock propagates to wages for the simplified baseline network and the baseline regional network, respectively. The graphs to the left can be used to compare the networks, with Panel (c) showing smaller CB units than Panel (b). The graphs in the middle show that the responses of the wage floor are very different across networks. In Panel (b), the CB unit with nodes to the right of the middle graph is the one with least responsive wage floors, whereas in Panel (c) the same CB unit shows the largest response. The graphs to the right show that wages are very responsive to their own shock, but they also illustrate that the differential changes in wage floors propagate the shock to less affected local labor markets.

Separating the network along regional lines results in very distinct responses of wages to the shock. One reason for this is that this leads to more homogeneous CB units in terms of productivity of covered local labor markets. Then, unions can be more responsive to shocks as the possibility of destroying jobs in low-productivity local labor markets is reduced. In the next subsection I compare different CB networks in terms of the responsiveness of wages to shocks across the entire labor market.

8.3 Shock Propagation and bargaining centralization

I explore how the degree of centralization of bargaining affects the propagation of shocks throughout the labor market. To summarize the degree of shock propagation, I simulate the equilibrium of the model pre- and post-shock for each network and compute the correlation between the local shocks and the local change in wages. I measure bargaining centralization with the mean number of local labor markets per CB unit. I also compute the standard deviation of wage floor changes and the share of firms bunching in the pre-shock equilibrium.

Panel (a) of Figure 12 shows the results. By construction, this correlation is one for a "local" network, where each local labor market is a separate CB unit. We observe a non-monotonic relationship between the correlation and the degree of centralization of bargaining. Although there is not a clean pattern, the data suggests a U-shaped relationship. Local and highly centralized bargaining result in a high correlation between shocks and wage changes or, in other words, a lower degree of propagation of shocks. While this is trivial for local bargaining, it is intriguing to see a low degree of shock propagation for highly centralized bargaining. On the other hand, bargaining with medium levels of centralization results in a lower correlation between shocks and wage changes. Overall, there is significant variability in the degree of shock propagation across networks.

What explains these patterns? A CB network will result in more shock propagation if negotiated wage floors have a large impact on the local labor market. Panel (b) of Figure 12 shows that wage floors are more responsive under more centralized CB networks. However, the impact of the wage floor on the local labor market depends on the share of firms that are bunching at the wage floor. Panel (c) of Figure 12 shows that more centralized networks result in a lower share of firms bunching at the wage floor on average. However, we note 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. By better aligning the level of productivity with CB units, this network results in a higher share of firms bunching at the wage floor and a higher degree of shock propagation.

8.4 Discussion

This is not the first paper to explore the effects of the centralization of bargaining. Calmfors and Driffill (1988) argue that extreme degrees of centralization of bargaining perform best in terms of macroeconomic performance.[24] The evidence for this theoretical prediction has been mixed (see Moene et al. 1993 for a review). Boeri et al. (2021) compare wage-setting institutions in Italy and Germany, and find that the more centralized Italian system results in higher unemployment in low-productivity regions. These papers emphasize the role of the level of wages.

I focus on a related question: whether the degree of centralization of bargaining affects the responsiveness of wages to shocks. Barth et al. (2023) find that the effect of import competition from China on employment was stronger in European countries with uncoordinated wage bargaining. The authors point out that wage coordination may work as an insurance device against the risk of shocks. My model does not allow for cross-union wage coordination, but it does incorporate a similar risk-sharing mechanism since wages are less responsive to shocks that affect a subset of local labor markets in the CB unit. Countries with coordinated bargaining also tend to have more centralized bargaining, so it is possible that the mechanisms proposed in this paper explain part of this result.[25] Ronchi and di Mauro (2017) find that firms in countries with more centralized bargaining faced stronger wage rigidity during the Great Recession, resulting in employment losses. This finding contradicts Barth et al. (2023), who find better employment performance in countries with more centralized bargaining. The interaction between the shock and the shape of the CB network may be key to understand these differences.

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. In the context of Argentina, my

[24] Their key insight is that medium degrees of decentralization will generate negative externalities in other sectors that are ignored by unions, whereas these negative effects will be internalized by the competitive forces of decentralized bargaining or by the bargains of a monopolistic union.

[25] The authors use a measure of wage coordination from Visser (2019). The dataset also provides a measure of the degree of centralization of bargaining that is positively correlated with wage coordination.

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 conditions, and are as a result more binding. This prevents concentrated local shocks from being fully transmitted to local wages, thereby dissipating their effects across the economy.

9 Conclusions

This paper studied the role of collective bargaining (CB) in mediating the effects of shocks. I find that firms respond to product-demand shocks to other firms in the same CB unit, indicating that shocks propagate through CB. The results are consistent with collective rent-sharing: when average economic conditions among covered firms improve, unions negotiate higher wage floors that affect wages and employment among all firms in the CB unit. Additionally, I find that wages respond more strongly to CB shocks than to comparable firm shocks. Although this result is robust across several specifications, it may not readily generalize to other settings. In particular, the strength of unions in Argentina and the frequent nominal wage adjustments during the study period could be factors that contribute to the strong response of wages to CB shocks.

The empirical findings suggest that CB may play an important role in mediating the effects of shocks in the labor market. However, they are uninformative about the effects of shocks under alternative CB networks. To study this question, I developed a structural model of the labor market with CB. The model illustrates how the CB network can affect the propagation of shocks, leading to a sharing of risk across firms. Interestingly, I find a U-shaped relationship between the degree of shock propagation and the degree of centralization of bargaining, suggesting that wage responsiveness to local shocks is lower with intermediate levels of centralization. This can be explained by the extent to which firms are constrained by the wage floor across CB networks.

This article opens up several avenues for future research. First, the article 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 abstracts from several features of labor markets that may be important to determine the role of CB in wage inequality, such as worker heterogeneity. Third, the analysis ignores potential effects of collective bargaining on informality, which may be particularly important in developing countries.

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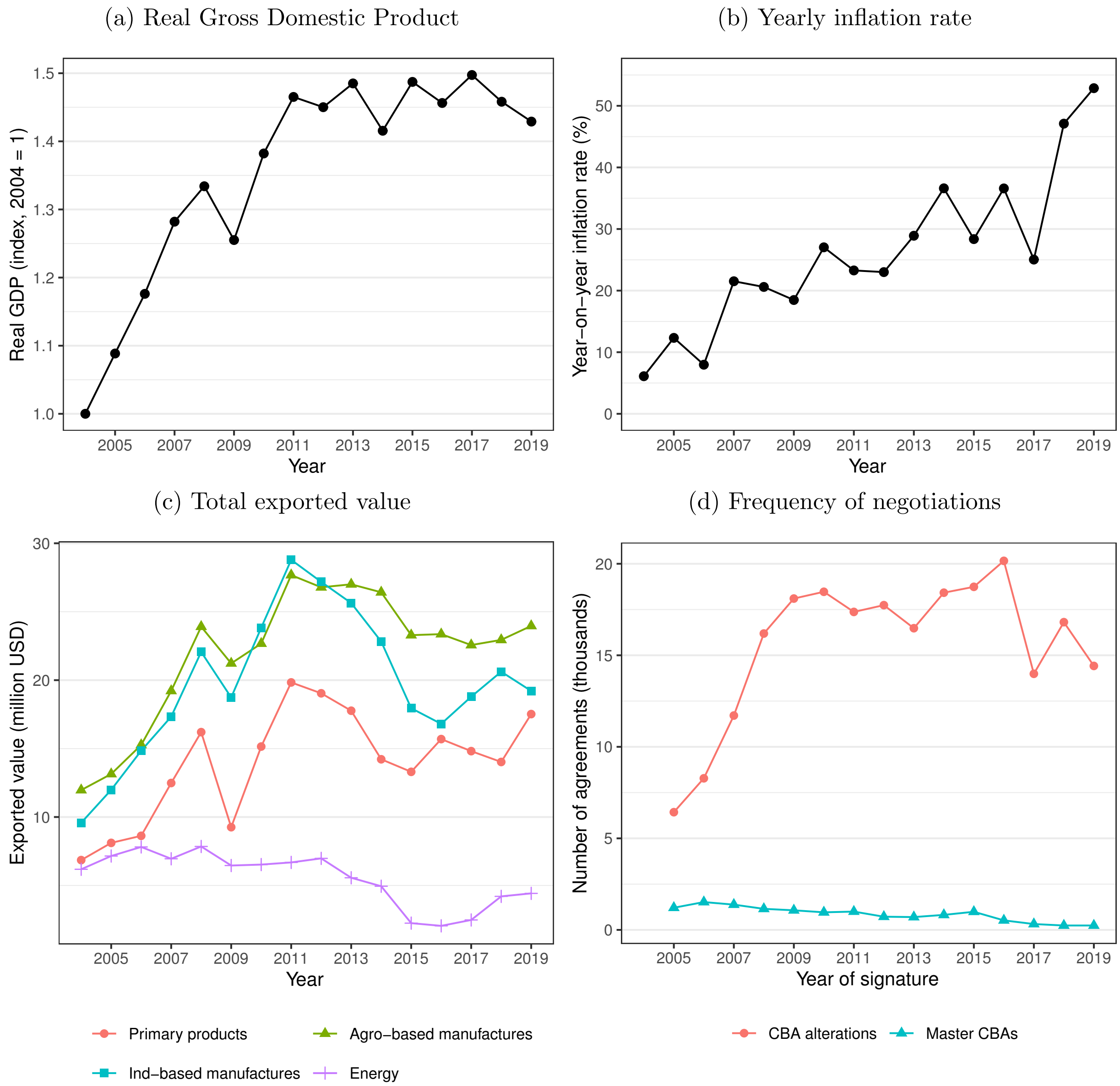
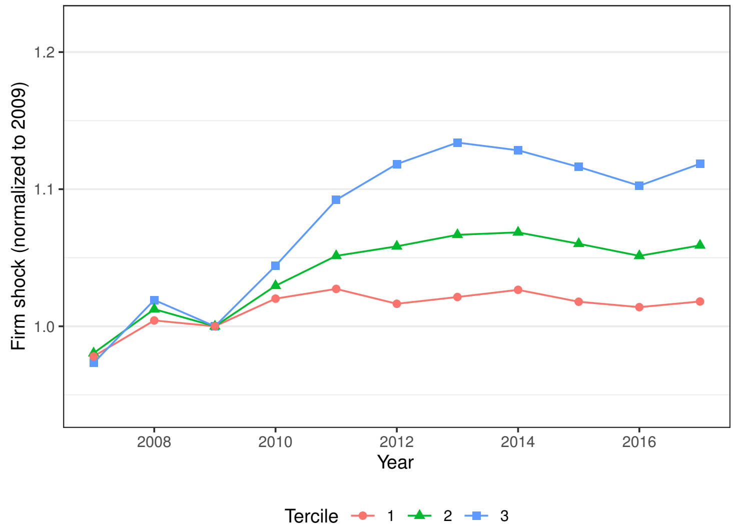
Figure 1: Performance of Argentine economy, 2004–2019



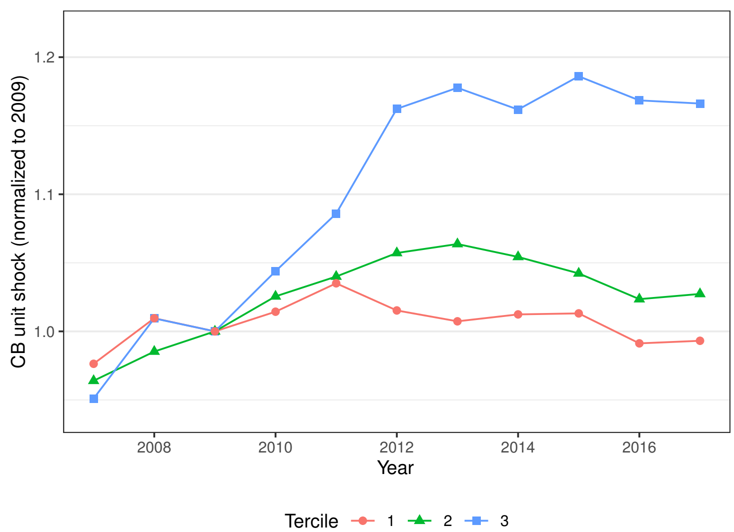
Notes: The figure shows the evolution of key macroeconomic variables in Argentina for the period 2004–2019. Panel (a) shows the evolution of the real gross domestic product (GDP), using data from the National Institute of Statistics and Censuses (INDEC). The real GDP is measured in constant 2004 Argentine pesos and normalized to 1 in 2004. Panel (b) shows the yearly inflation rate constructed from INDEC, and using data from regional statistics offices for the period 2007–2015. The inflation rate is measured as the yearly percentage change in the consumer price index as of December of each year. Panel (c) shows the total exported value, using data from INDEC. The total exported value is measured in millions of current US dollars. Panel (d) shows the number of collective bargaining agreements (CBAs) signed each year, using data obtained from the public archive of Collective Bargaining Agreements.

Figure 2: Evolution of export shocks to firms and collective bargaining units

(a) Shocks to firms



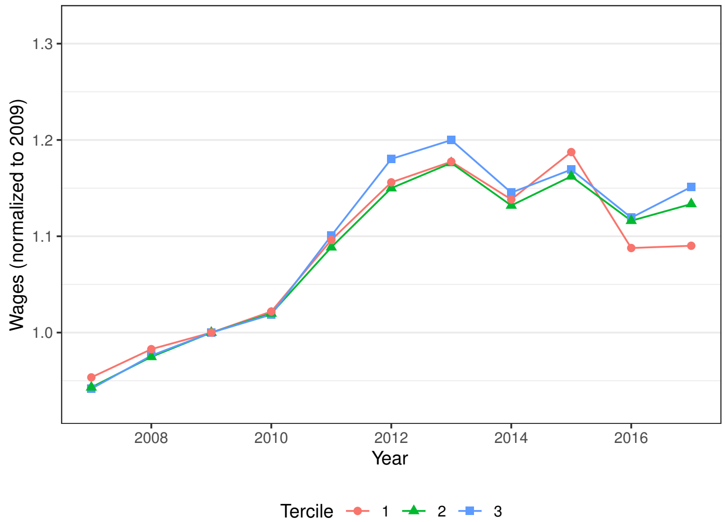
(b) Shocks to CB units



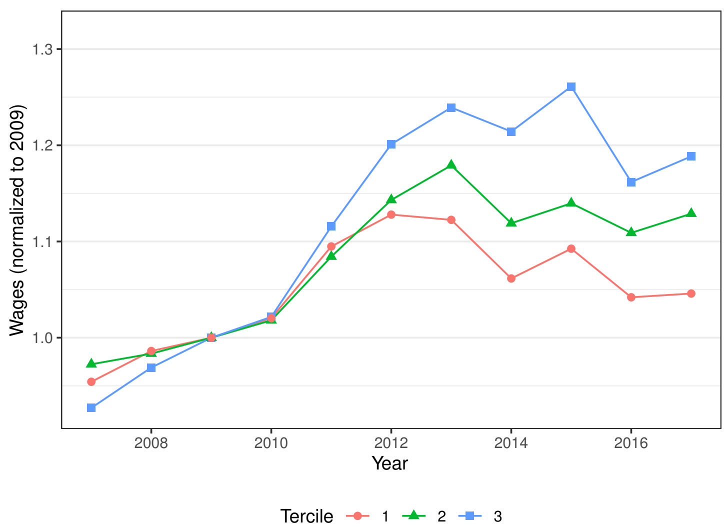
Notes: Data are from the baseline sample of exporting firms. The figure illustrates the evolution of time-varying firm and CB shocks, for different levels of the static firm and CB shocks. Each line depicts the average of the time-varying shock in a given tercile of the distribution of the static shock. The time-varying versions of the shocks are constructed as averages in world import demand in a given year, weighting by appropriate exposure shares, and then normalized by the 2009 value. The static shocks are constructed from the average change in world import demand for a given country-product between 2009–2010 and 2012–2013, also weighted by exposure shares. Firm exposure shares are equal to the share of a firm's exports in a given country-product. CB exposure shares are defined as the sum across firms of the employment share of a firm in the CB unit times the firm's value exported share. The averages in Panel (b) are weighted by the number of firms in a given CB unit.

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

(a) Shocks to firms



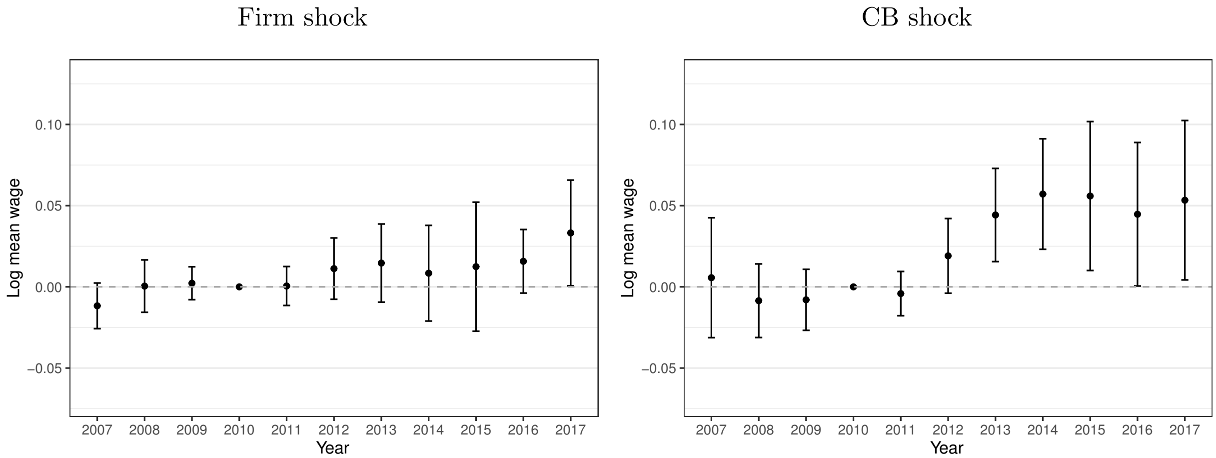
(b) Shocks to CB units



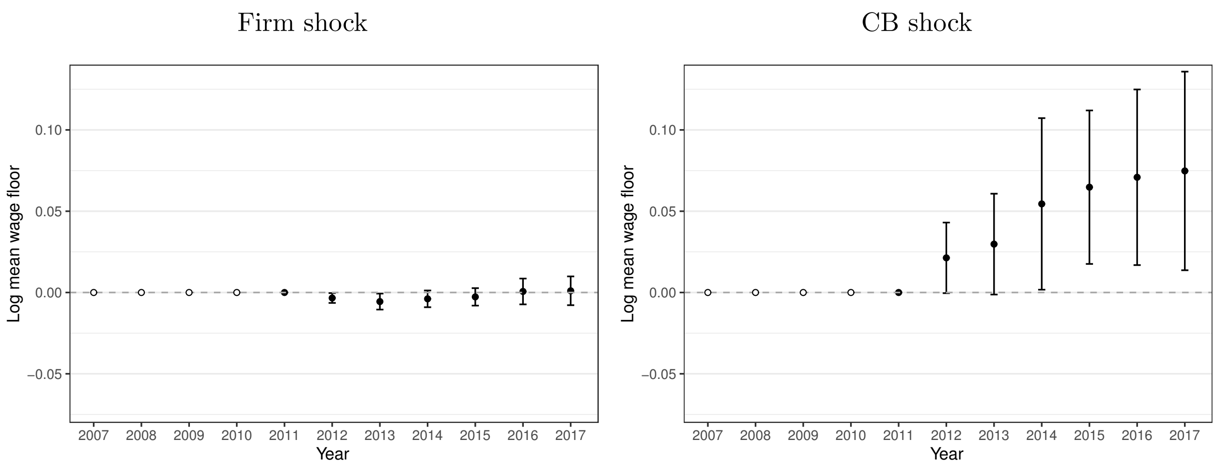
Notes: Data are from the baseline sample of exporting firms. The figure shows the average evolution of mean wages for firms in different terciles of the distribution of the firm shock (Panel a) and the CB shock (Panel b), relative to 2009. The firm and CB shocks are defined as the average changes in world import demand between 2009–2010 and 2012–2013, weighting by appropriate exposure shares.

Figure 4: Effect of export shocks on mean wages and mean wage floors

(a) Log mean wages

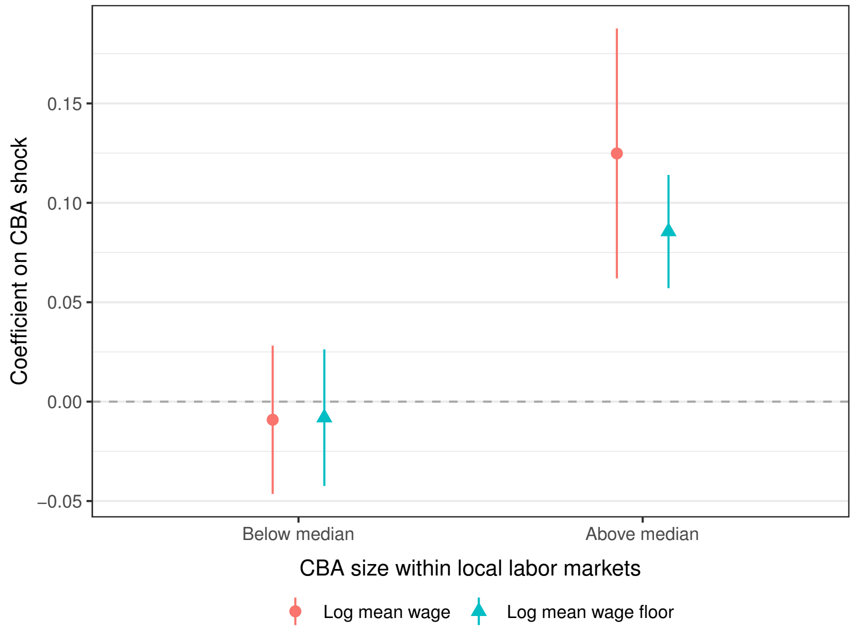


(b) Log mean wage floors



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 mean wage floors, interacting the shocks with year dummies. The regression omits the year 2010 for the wage variable, and the year 2011 for the wage floor variable. The regression includes firm fixed effects, 4-digit economic sector by province by year fixed effects, time-varying 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 and CB shocks are defined as the average changes in world import demand between 2009–2010 and 2012–2013, weighting by appropriate exposure shares. Standard errors are clustered at the CB unit level.

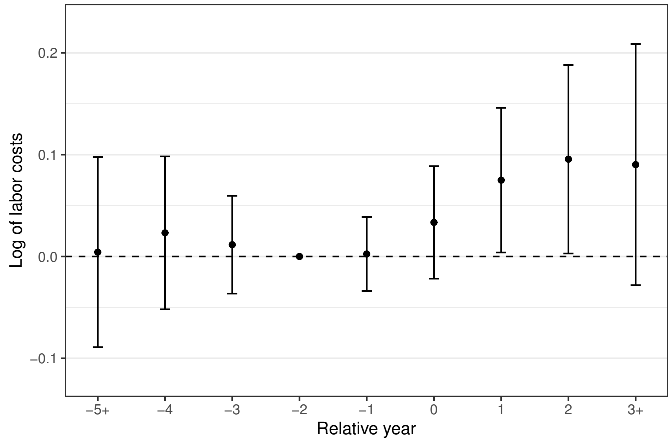
Figure 5: Effect of export shocks to CB units on wages, by size of CB unit



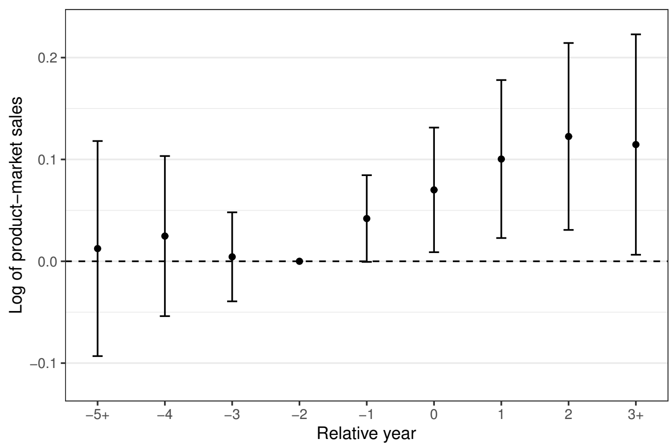
Notes: Data are from the baseline panel of exporting firms, excluding province by 4-digit sector cells with less than 2 CBAs. The figure shows estimates of the effects of CB shocks on log mean wages and log mean wage floors, interacting the CB shock with an indicator for the size of the CB unit. Estimation is done using a static difference-in-differences strategy as in Table 2, but interacting the local labor market fixed effects with an indicator for the size of the CB unit. Standard errors are clustered at the CB unit level.

Figure 6: Effect of firm shocks on firm's accounting outcomes, panel event-study design

(a) Log wage expenditures



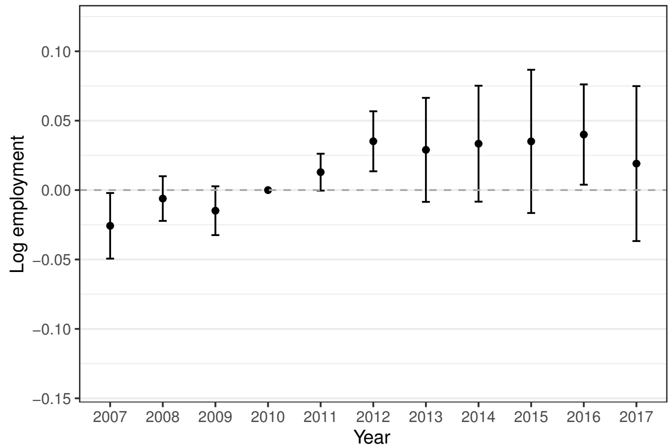
(b) Log product market sales



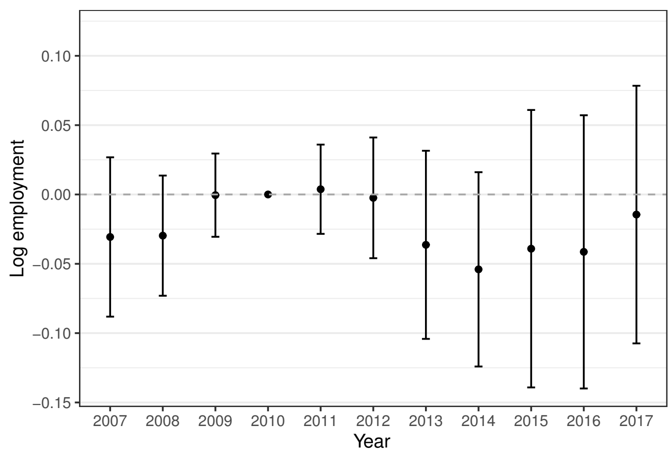
Notes: Data are from a sample of firms that exported in 2011–2012 that were surveyed in the first or second waves of the *Encuesta Nacional de Dinámica del Empleo y la Innovación* (ENDEI). The figure shows coefficients on the effect of firms shocks on a firm accounting outcomes, using a panel event-study design as described in Appendix E. The time-varying firm shock z_{jt} is defined as the average world import demand across the country-products exported by the firm in 2011–2012, weighting by the share of the value exported to each country-product. 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 7: Effect of export shocks on employment

(a) Firm shock



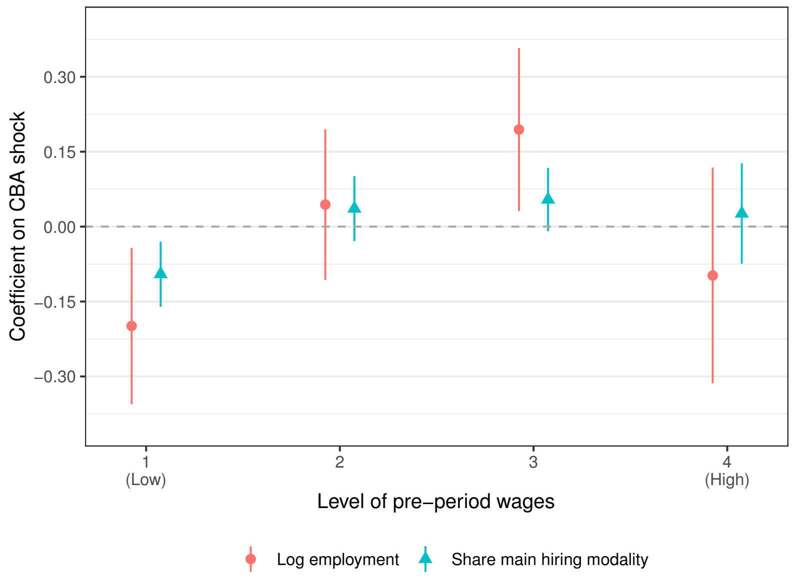
(b) CB shock



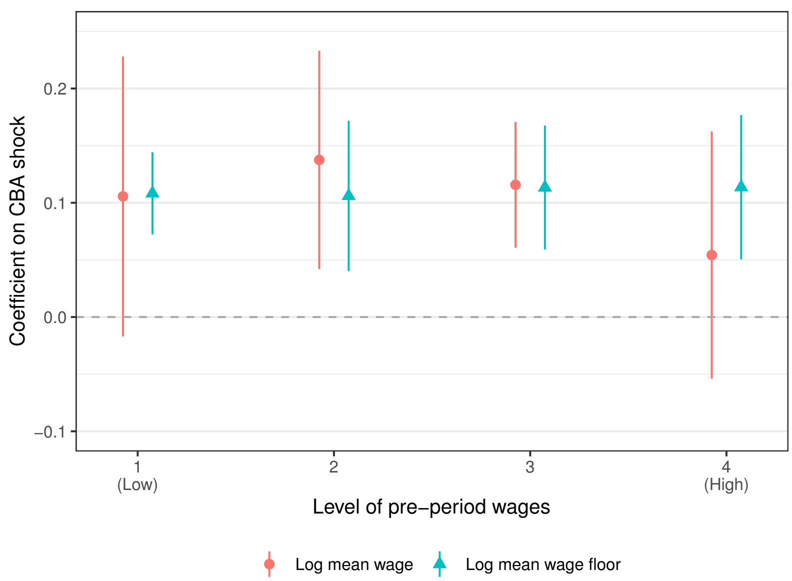
Notes: Data are from the baseline sample of exporting firms, including only firm-years for which wage floors are available. The figure shows the dynamic effects of firm and CB shocks on log employment, interacting the shocks with year dummies and omitting the year 2010. The regression includes firm fixed effects, 4-digit economic sector by province by year fixed effects, time-varying 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 and CB shocks are defined as the average changes in world import demand between 2009–2010 and 2012–2013, weighting by appropriate exposure shares. Standard errors are clustered at the CB unit level.

Figure 8: Effect of export shocks to CB units, heterogeneity analysis

(a) Employment outcomes



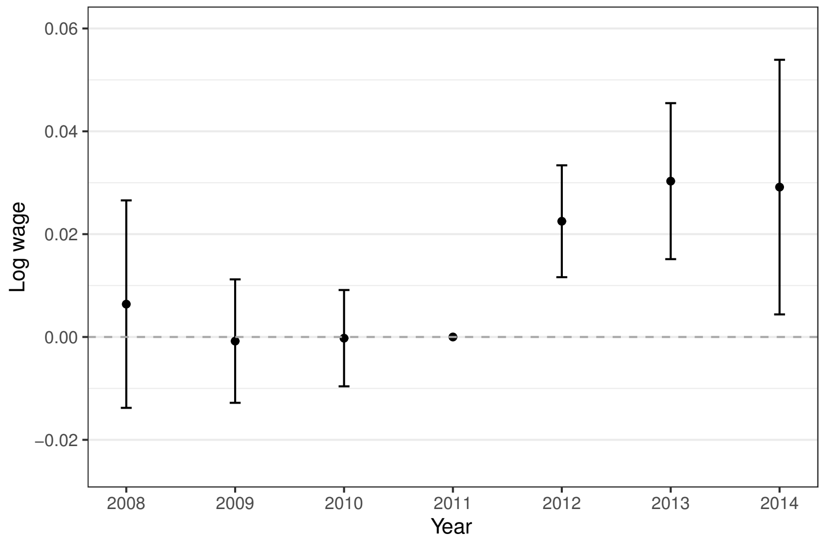
(b) Wage outcomes



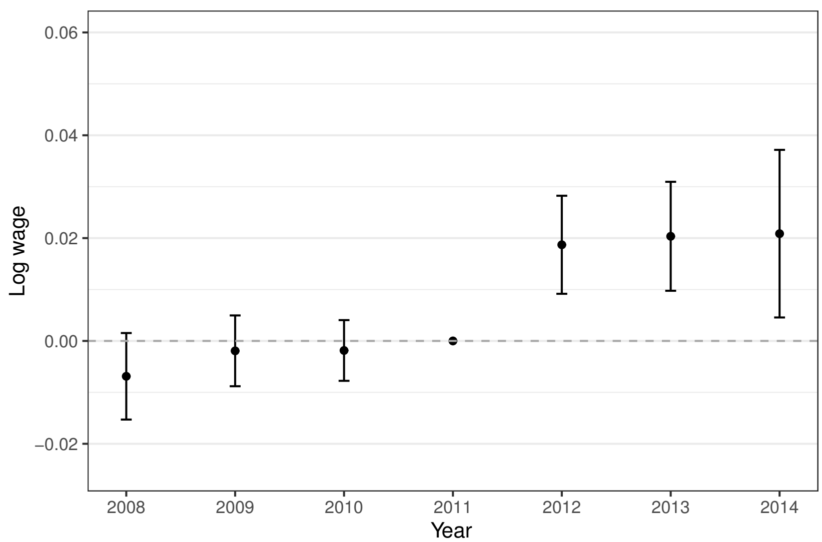
Notes: Data are from the baseline sample of exporting firms, excluding CB unit by province cells with less than 8 firms. The figure shows estimates of the effects of CBA shocks on a given outcome interacted with dummies for different quartiles of the pre-period level of wages (2007–2009), defined within 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 probability 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 2, but interacting the local labor market by year fixed effects with indicators for the different quartiles of the pre-period level of wages. Standard errors are clustered at the CB unit level.

Figure 9: Effect of export shocks to CB units, worker-level estimates

(a) Shock to firm's primary CB



(b) Shock to worker's CB unit, controlling for firm time-varying shocks

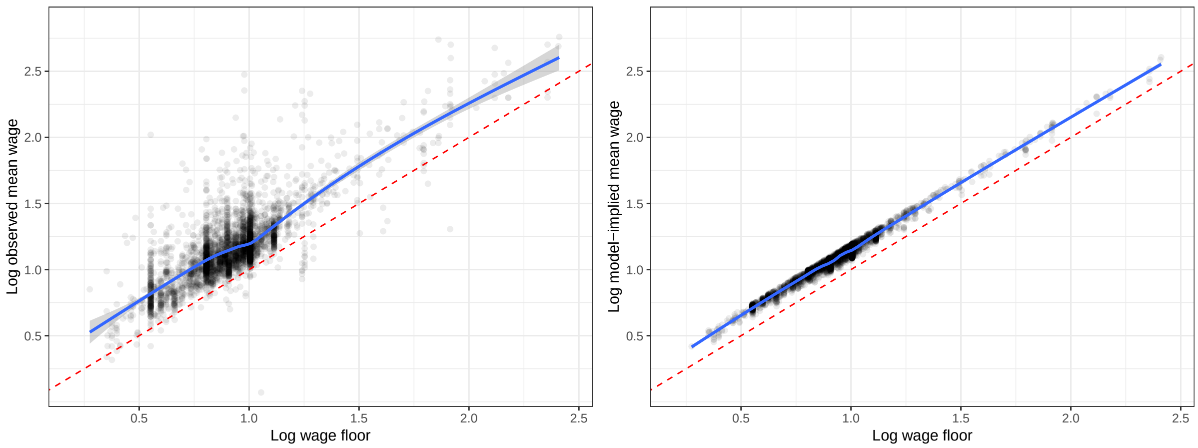


Notes: Data are from a panel of workers that worked in 2008, 2011, and 2014 in a firm in the baseline sample. The figures show estimates of the effect of CB shocks on mean monthly wage. Panel (a) estimates a difference-in-differences model using the primary CBA of the firm to define the treatment. It 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. Panel (b) 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. Standard errors are clustered at the CB unit level.

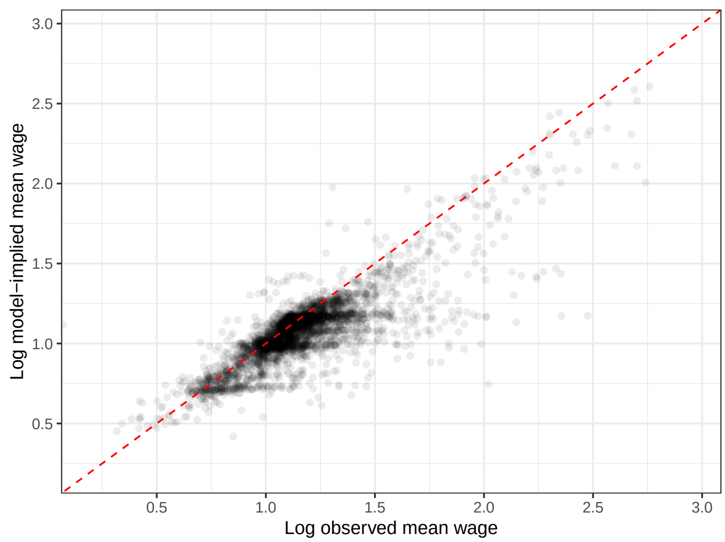
Figure 10: Summary of model fit to the data

(a) Wage floor versus average wage

In the data | In the model



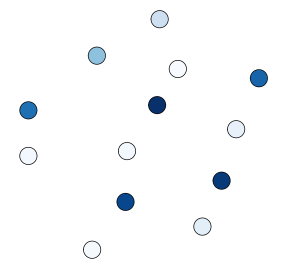
(b) Wages in the data versus in the model



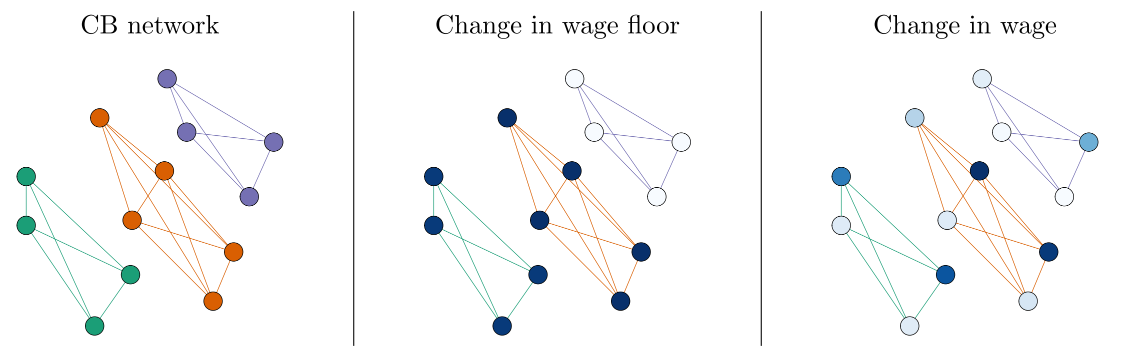
Notes: The figure illustrates the model fit to the local labor market data. Panel (a) shows a scatter plot of observed mean wages versus model-implied mean wages in each local labor market. Panel (b) shows the correlation between the log wage floor and the log mean wage. The left column shows the data, the right column shows the model.

Figure 11: Illustration of bargaining networks and shock propagation, model-simulated data

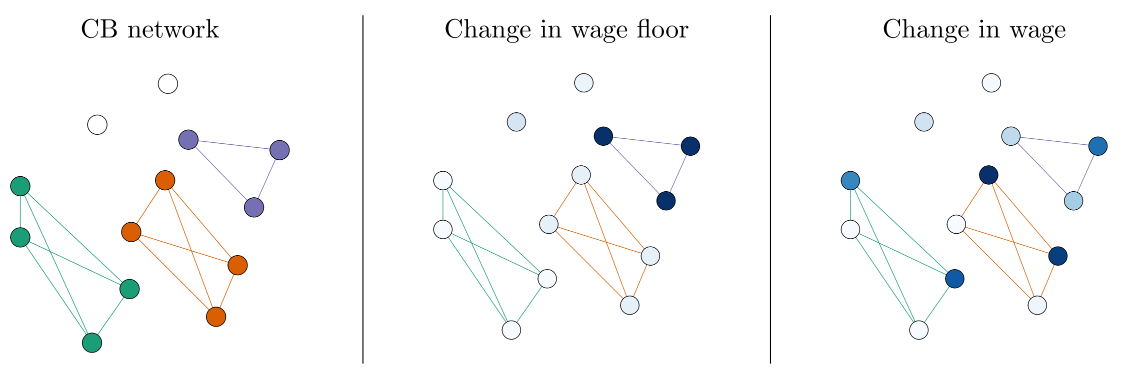
(a) Change in revenue



(b) Baseline network



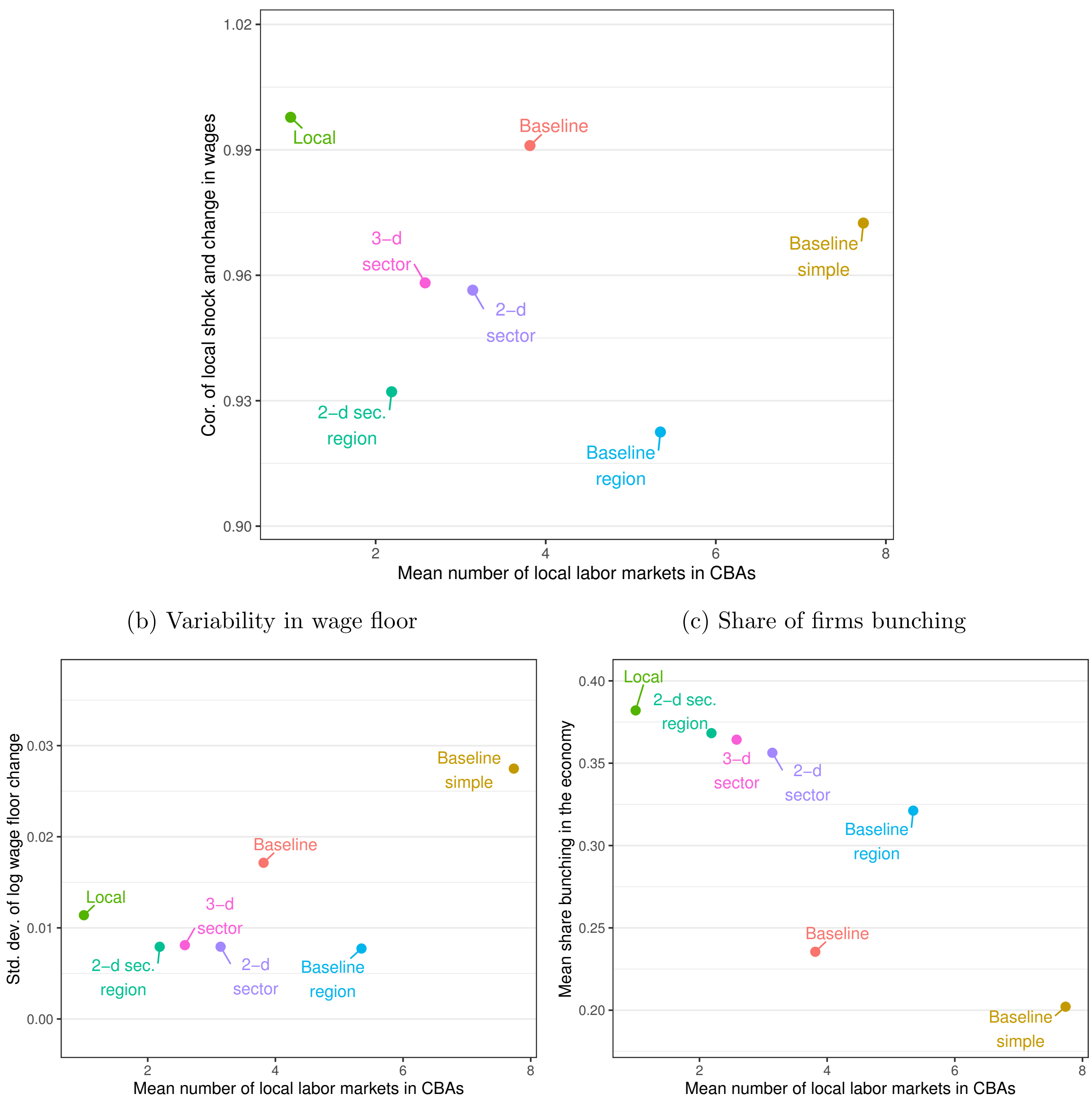
(c) Baseline regional network



Notes: The figure illustrates the propagation of shocks to wages across different collective bargaining (CB) networks. Each node represents one local labor market in the sectors "Manufacture of pesticides and other agrochemical products" and "Manufacture of soap and detergents, cleaning and polishing" (ISIC codes 2021 and 2023, respectively). Local labor markets also vary in terms of the region and their exporting status. In Panel (a), nodes depict local labor markets, with the color intensity indicating the revenue change following the export shock. For Panels (b) and (c), the left graph colors nodes based on the CB network, the middle graph colors nodes based on the change in the log wage floor, and the right graph colors nodes based on the change in the log wage. Panel (b) shows a simplified version of the baseline network that assigns the modal sectoral CB unit to small local labor markets that bargain locally in the baseline network. Panel (c) shows a baseline regional network that splits the CB units according to the region. The edges in each graph connect local labor markets that belong to the same CB unit. Color palettes are defined separately for each graph.

Figure 12: Centralization of bargaining and shock propagation

(a) Degree of shock propagation



(b) Variability in wage floor

(c) Share of firms bunching

Notes: The figure shows the relationship between the average number of local labor markets in a CB unit and several outcomes obtained from model-simulated data. Panel (a) shows the correlation between shocks and wage changes across local labor markets. Panel (b) shows the standard deviation of the wage floor across local labor markets. Panel (c) shows the average share of firms bunching in the economy. 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: Description of coverage of selected collective bargaining agreements 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 (CBAs) in the textile industry. The three CBAs specify the entire country as their regional scope, and were signed by different unions. 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.* 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.

Table 2: 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 × Post	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 × Post	0.0173	-0.0026	0.0168	0.0389	0.0043	0.0002
	(0.0117)	(0.0022)	(0.0119)	(0.0176)	(0.0059)	(0.0043)
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	7,600	7,330	7,330	7,600	7,600	7,600
Num. fixed effects	19,607	14,604	14,604	19,607	19,647	19,799
Num. observations	81,778	48,606	48,602	81,778	82,221	83,600
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 firm and CB shocks are defined as the average changes in world import demand between 2009–2010 and 2012–2013, weighting by appropriate exposure shares. 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. Standard errors are clustered at the CB unit level.

Appendix

A Proofs for Theoretical Framework

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

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

where $w_j = \underline{w}$ 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 $j \in \mathcal{J}^{\text{co}}$. I will add and subtract terms to drop the terms involving f_ℓ. I also substitute $d\underline{w} = \underline{w} d\ln\underline{w}$ and $d\varphi_j = \varphi_j d\ln\varphi_j$, and construct 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

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

Defining the elasticity of the wage bill as $\iota_j = \rho_j^{\ell}$ for constrained firms and $\iota_j = (1+\eta_j)\,\rho_j^w$ 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

$$R\left(\frac{d\omega}{d\underline{w}_c} + \sum_j \frac{d\omega}{d\varphi_j}\right) = R\omega(1-\beta)\left(\frac{d\left[\left(-\frac{d\Pi}{d\underline{w}}/\frac{dU}{d\underline{w}}\right)\right]}{d\underline{w}} + \sum_j \frac{d\left[\left(-\frac{d\Pi}{d\underline{w}}/\frac{dU}{d\underline{w}}\right)\right]}{d\varphi_j}\right), \tag{A.3}$$

where $R = \sum_j \varphi_j f(\ell_j)$ is the aggregate revenue. After the corresponding algebraic manipulations, the final expression will resemble equation (4) but with an additional term that corresponds to A.3 divided by $\tilde{WB}^{\text{co}}$.

□

Proof of Proposition 2. The results follow from the effects of the wage floor on firms discussed in Section 2.1. □

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 are regarded as minimum standards for workers that individual firms cannot modify to their detriment.

Types of unions. In Argentina, there is freedom of association, which enables any group of workers 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 agglomerate federations and basic unions.

Despite this freedom of association, not all unions are legally allowed to negotiate CBAs. Only one union per "area of representation" is endowed with "bargaining privileges." 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*): its most important CBA (0130/75) 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 and coverage. 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 requests them. Areas of representation effectively delimit the scope of collective bargaining units. 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, especially in sectors exposed to international trade. CBAs signed within these areas of representation are binding for all workers and firms within them. 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.

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 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

[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.

some provisions within it. While master CBAs have an expiration date, even if they are not renegotiated they remain in force until a new master CBA replaces them. CBA alterations act as amendments to the master CBA and are negotiated more frequently. They typically relate to updates in wage scales, although they may also entail modifications in other provisions.

The dynamics of negotiations. Panel (d) of Figure 1 shows the dynamics of collective negotiations in 2005–2019. After a period of low activity in the 90s, the number of negotiations reignited in the early 2000s.[4] 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, galvanizing unions that had not negotiated in many years into signing new master CBAs. These factors account for the peak of 150 new master CBAs signed in 2006. 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. In fact, we observe a large increase in CBA alterations that persisted throughout the entire period.[5]

B.2 Data

B.2.1 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. While the dataset does not contain information on hours or full-time status, it does contain a "hiring modality" variable that can be used as a proxy. This variable contains tens of categories, but the most common one, number 8, usually corresponds to full-time workers employed under a permanent contract. As suggested by the distributions of wages discussed in Appendix C, sometimes part-time workers are declared also under the main category.

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

[4]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.

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

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 B.1 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.

Appendix Table B.1: Mandatory usage of *Simplificación Registral* by firm employment

Period	**Threshold (employment)**
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.

Importantly, both datasets contain the same worker and firm identifiers. As a result, I can use *Simplificación Registral* to add information on the CBA code to the matched employer-employee dataset. I describe the processing of the CBA code variable later in this appendix.

B.2.2 Other data sources

First, I collected data from the publicly available BACI-CEPII dataset (Gaulier and Zignago 2010), which contains yearly trade flows 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. Second, I obtained administrative data from Argentine customs (*Dirección General de Aduanas*) which details the value exported to each country and product for every Argentine 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.[6] I use names to match country codes between the Customs data and BACI-CEPII. Then, I join the datasets using the country codes and the HS codes.

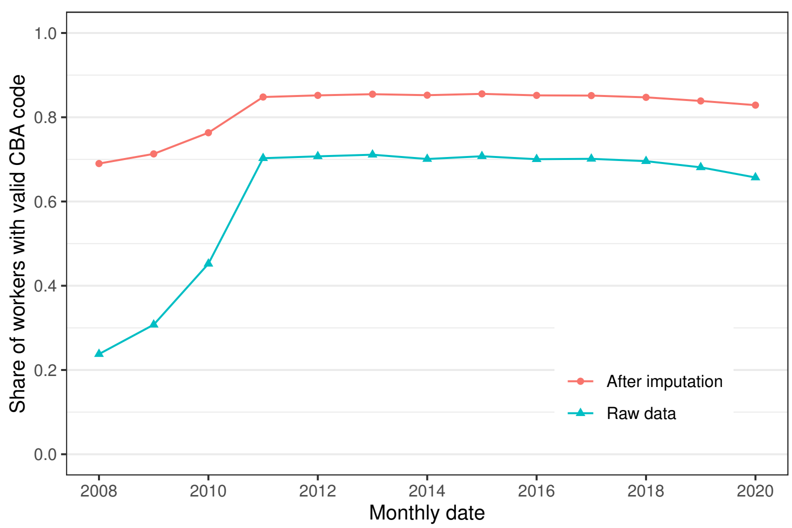
[6] To convert codes I proceed as follows. First, I convert NCM 8-digit to NCM 6-digit by keeping the first 6 digits. These 6 digits directly correspond to the HS, although not necessarily the 2007 version. I then convert codes in different years to HS 6-digit version 2007 using the appropriate concordance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

To study how a firm's accounting outcomes 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.

B.2.3 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 but still reflect the same CB unit. To increase the number of workers with a CBA code and update the codes I do the following.

Appendix Figure B.1: Share of workers with non-missing CBA 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.

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 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 B.1 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 CB units. For firms employing workers across multiple CBAs, I assign as primary CBA code the modal CBA code. These primary CBA codes correspond to CB units. 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.[7] 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. Then, I smooth the resulting time series of wage floors to reduce noise.

Figure C.2 shows the distribution of wages for two categories of a given CBA, CBA region, and month. 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.[8] We also observe a smaller bunching point at around half the wage floor, which corresponds to workers that actually work part-time and as a result earn half the wage floor.

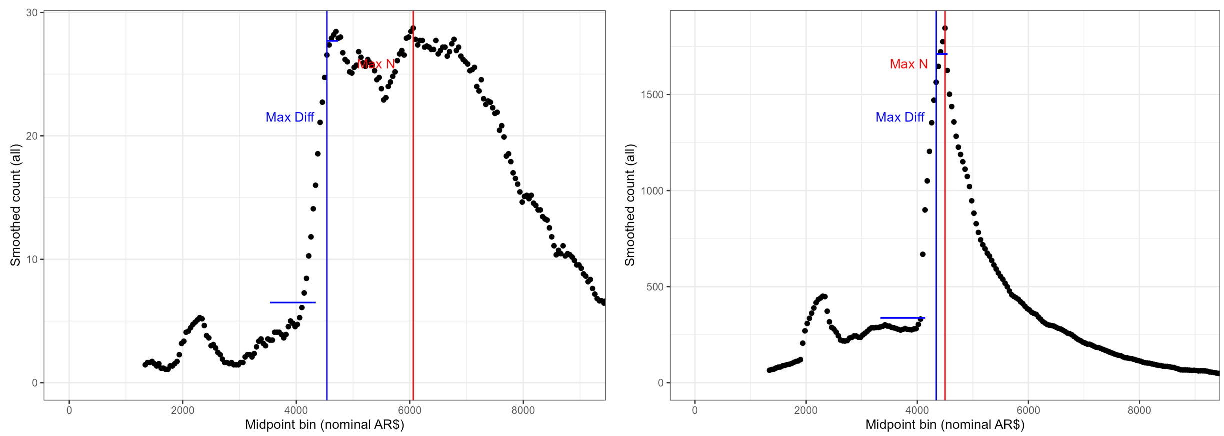
The goal is to identify the bunching point. One possible way is to simply pick the mode of the distribution. However, as shown by the left panel of Appendix Figure C.2, the mode may be higher than the wage floor. A second option is to pick the point at which the distribution increases more rapidly. I implement this approach by selecting the bin at which the difference between a 20-bin average and the subsequent 5-bin average is maximized. This is the preferred

[7] 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.

[8] 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.

approach as it seems to capture the actual wage floor in a variety of cases in which the mode is not a good approximation.

Appendix Figure C.2: Illustration of the distribution of wages within a CBA, category, CBA region in January 2012



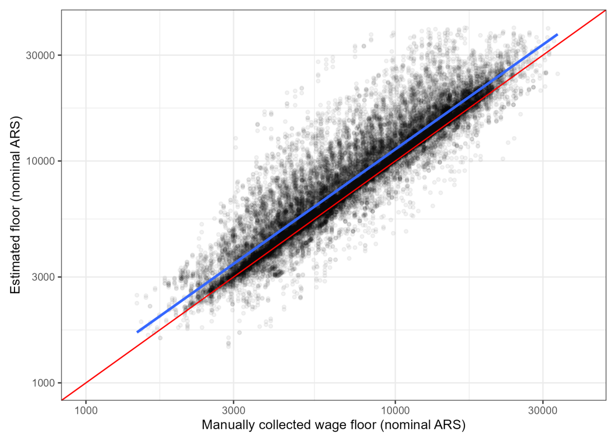
Notes: The figures show the distribution of wages within a CBA, category, CBA region, and month. The bins are equal to 20 pesos in 2012, but change with the inflation rate in subsequent years. The bins were smoothed using a moving average with a window of 5 bins at each side. The blue line shows the "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 estimated wage floors from CBAs with few workers. 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.

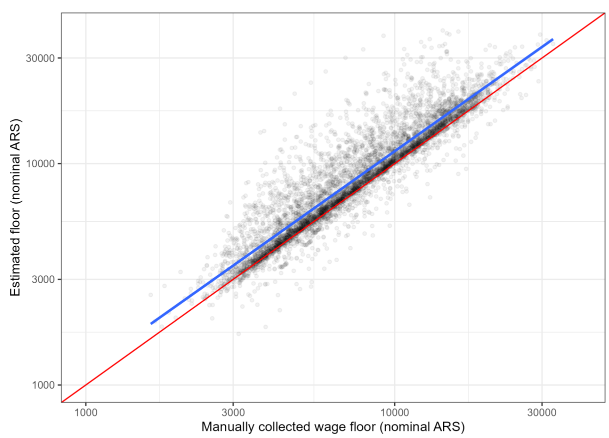
Appendix Figure C.3 shows a comparison between manually collected wage floors and the wage floors inferred from the distribution of wages. The manual collection is challenging as it requires reading the actual agreements, which are usually in PDF format and do not follow a consistent structure over time. 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 the update of the wage scales in a given month, then the collected wage floor would appear to jump by a larger amount in the next monthly update.

Appendix Figure C.3: Validation of wage floors with manually collected wage floor data

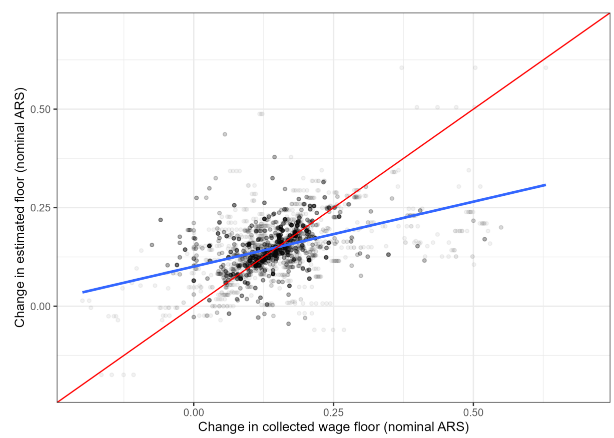
(a) Monthly comparison



(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.

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.

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

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

where s_{jpn} are exposure shares (with $\sum_{p \in \mathcal{P}} s_{jpn} = 1$), and f_p are common product-demand shocks.

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 a quasi-randomness assumption on the product-demand shocks can be applied. Let $\mathcal{J}$ be the set of firms. The full-data moment conditions that identify β_1 and β_2 in (D.1) 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 equivalently written as

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

Note that we can also write each of these expressions as

$$
\begin{aligned}
&\mathbb{E}\left[\frac{1}{|\mathcal{J}|}\sum_{j'\in\mathcal{J}}\tilde{z}_{j'n}\left(\Delta\tilde{y}_{j'}-\tilde{\beta}_1\tilde{z}_{j'1}-\tilde{\beta}_2\tilde{z}_{j'2}\right)\right]\\
&=\mathbb{E}\left[\frac{1}{|\mathcal{J}|}\sum_{j'\in\mathcal{J}}\left(\sum_{p\in\mathcal{P}}\tilde{s}_{jpn}f_p\right)\left(\Delta\tilde{y}_{j'}-\tilde{\beta}_1\tilde{z}_{j'1}-\tilde{\beta}_2\tilde{z}_{j'2}\right)\right]\\
&=\mathbb{E}\left[\sum_{p\in\mathcal{P}}f_p\frac{1}{|\mathcal{J}|}\sum_{j'\in\mathcal{J}}\tilde{s}_{jpn}\left(\Delta\tilde{y}_{j'}-\tilde{\beta}_1\tilde{z}_{j'1}-\tilde{\beta}_2\tilde{z}_{j'2}\right)\right]\\
&=\mathbb{E}\left[\sum_{p\in\mathcal{P}}f_p r_{pn}\left(\tilde{\beta}_1,\tilde{\beta}_2\right)\right],
\end{aligned}
$$

where $n\in\{1,2\}$ indexes each condition, $\tilde{\beta}_1$ and $\tilde{\beta}_2$ are parameters, and $r_{pn}\left(\tilde{\beta}_1,\tilde{\beta}_2\right)=(1/|\mathcal{J}|)\sum_{j'\in\mathcal{J}}\tilde{s}_{j'pn}\left(\Delta\tilde{y}_{j'}-\tilde{\beta}_1\tilde{z}_{j'1}-\tilde{\beta}_2\tilde{z}_{j'2}\right)$ is an average residual for each country-product p. Setting these expressions equal to zero defines a country-product-level GMM problem dual to (D.1).

The identification question is whether the parameters β_1 and β_2 can be identified from the country-product-level GMM problem. Given our reasoning, it is clear that $\tilde{\beta}_n$ will equal β_n for $n\in\{1,2\}$ if and only if $E\left[\sum_{p\in\mathcal{P}}f_p r_{pn}(\beta_1,\beta_2)\right]=0$. These conditions will be satisfied under assumptions in the spirit of Assumptions 1 and 2 in Borusyak et al. (2022b). In particular, the key sufficient condition for identification is that $E\left[f_p|r_{p1},r_{p2}\right]=0$, which amounts to a quasi-randomness assumption on the product-demand shocks f_p. 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.

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 equation (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:

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

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.[9] Similarly, past values of the z's (i.e., lagged values up to $\underline{R}$ years) identify the dynamic effects of the treatment.

I use this strategy in Figure 6, where I set $\underline{R} = 4$ and $\overline{R} = 3$. Since my data runs from 2007 through 2010, this allows me to compute an entire set of event-study coefficients for any firm in the survey data in 2010–2012 or 2014–2016. For those observed in 2010, I compute post-coefficients using data starting from $2010 - \overline{R} = 2007$, and for those observed in 2016, I compute pre-coefficients using data up to $2016 + \underline{R} = 2020$. 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

[9] 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.

r who optimally choose firm j is given by

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

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 Appendix D in Parente (2022).

F.1.2 Labor supply: Formal employment decision

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

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

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

F.1.4 Local labor markets: derivations

Recall that the cdf of productivity is $F_g(\varphi) = 1-(\varphi/\varphi_{g0})^{\alpha}$ if $\varphi > \varphi_{g0}$ and zero 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 $L_g = M_g \int_{\varphi_{g0}}^{\infty} \ell(\varphi) f_g(\varphi) d\varphi$. 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 CB 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 φ 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:

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

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.[10]

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 occur if, starting from a non-binding wage floor, an increase in the floor decreases the wage bill and thus the problem's objective function. This could be due to either general equilibrium effects or because some low productivity local labor markets are fully constrained by the wage floor and experience negative wage floor effects. These convex regions are problematic if they result in multiple maxima, which occurs in a knife-edge case where the level of utility with a non-binding wage floor is equal to the level of utility of a binding wage floor that is also a local maximum.

In summary, the Nash-in-Nash problem has a unique solution if all objective functions in the Nash-in-Nash problem are concave. In the case some objective function has a convex region, the problem has multiple equilibria only in a knife-edge case that is unlikely to occur in practice.

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

[10]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 previous wage floors vector.
3. Iteratively find equilibrium wage floors $\{\underline{w}_c^1\}$ numerically solving 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. I set as criteria that the mean absolute difference between consecutive iterations is less than 10^{-8}, both for the fixed-point iteration and for the entire loop.

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 particular, 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, defined in equation (2). However, as the FOC may not always hold in a maximum, I select several candidate points for maximizers and then evaluate the objective function to select the global maximum.

The first issue with the FOCs is that the derivatives of the wage bill and revenue are discontinuous when $\varphi_{g0} = \underline{w}_c$. Fortunately, this happens only in a small share sectors, usually belonging to the largest CB units. 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 $\varphi_{g0} = \underline{w}_c$ for some g as candidate points for maximizers.

Second, when there are multiple local labor markets in a CB unit, the objective functions are sums of terms, some of which do not depend on the wage floor (the unconstrained ones). Because derivatives are discontinuous, when a local labor market enters this sum the FOC may change discontinuously, generating the possibility of local optima. 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 candidate points and pick the one that yields the global maximum. When evaluating the objective function I adjust wage indexes to account for general equilibrium effects.

F.3 Defining local labor markets and summarizing data

The coarsening of 4-digit sectors attempts to prevent detailed sectors with too few workers.[11] 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 in three steps. First, I allow for the largest provinces in each region if the number of firms is high, which may have different CB units.[12] Second, I allow for separate local labor markets if firms are exporters. Third, I split regions based on the observed CB network, using the firm's "primary CBA" as defined in Appendix B.2.3. If a non-exporting cell has a number of firms or employment below several thresholds I assign it to a "local" CB unit.[13] Finally, if a local CB unit has less than 20 workers or fewer than 2% of workers have a wage floor assigned to them, I impute the modal CB unit in the region-sector cell.

I estimate wage floors by taking the mean of the firm-level average wage floor in each CB unit. I allow regional wage floors within a CB unit only if the region's average wage floor is sufficiently different from the rest. 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 CB units 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 CB unit to be determined in the negotiations. This aligns with usual practice in Argentina, where regional differences within CBAs are usually constant.

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

[11] I create a separate 4-digit code within each 1-digit sector to group a small percentage of firms that end up in 4-d sectors with less than 30 workers, or less than 2.5 of workers with an assigned wage floor.

[12] In "Centro," I allow for the City of Buenos Aires and the province of Buenos Aires if there are more than 250 firms, and for the Santa Fe and Cordoba if there are more than 300 firms. In "Norte," I allow for Tucuman, Salta, and Misiones if there are more than 300 firms. In "Cuyo," I allow for Mendoza if there are more than 150 firms. In "Patagonia," I allow for Santa Cruz, Chubut, and Tierra del Fuego if there are more than 150 firms as well.

[13] Specifically, I assign a local CB unit to a non-exporting cell if either of the following holds: less than 5 firms, less than 10 firms and less than 100 employees per firm, less than 30 firms and less than 30 employees per firm, less than 5 firms or 100 employees and less than 1% of employment in the CBA.

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.[14] I drop firms with a large share of these workers to compute local labor market quantities. Finally, there are many workers for which I do not observe both the CBA code and the occupation category.

The share of firms constrained is defined as the share of firms with a mean deviation from the wage floor of zero. When a local labor market has a large share of workers without a wage floor, I impute the share bunching using a regression model. I 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 10 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 $\eta = 4.0995 \approx 1/0.2439$. 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

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

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 10 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 11, 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 $\{\varphi_{g0}\}_{g\in\mathcal{G}}$. First, if the share of firms constrained by the wage floor is zero, then I set $\varphi_{g0} = (\eta/(\eta+1))\underline{w}_c$. 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 $\varphi_{g0} = \underline{w}_c$. 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) to get

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

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

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.[15] Then, equation (7) is used to obtain V_r. Finally, I compute b_r inverting equation (8). Appendix Table 11 shows the results.

Bargaining power parameters. I invert the closed form expression for the Nash bargaining solution of each CB unit 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. 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. This condition may not hold if a CB unit's optimum is not found at an interior solution.

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 14. Panel (b) of Appendix Figure 14 shows the estimated bargaining power parameters.

I check whether the inverted bargaining power parameters actually result in maximizers of the Nash bargaining objective functions. To do so I test whether the wage floor can be recovered from the model equilibrium using the bargaining power parameters. While I do recover the correct wage floor in most cases, for one important CB unit I do not: the retail CB unit 0130/75. For this CB unit the condition that delivers the bargaining power parameter is a local maximum, but for this bargaining power parameter the global maximum is a non-binding wage floor. To deal with this issue I keep fixed the wage floor of this CB unit in counterfactual exercises.

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

G Additional Tables and Figures

Appendix Table 1: 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 2: 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 3: 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 4: 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, The sample is analogous to the one in Table 2, but excludes CB unit by province cells with fewer than 8 firms. 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, respectively. The regression models include the firm shock, and also control for the same variables as Table 2. Standard errors, included for the hypothesis testing, are clustered at the CB unit level.

Appendix Table 5: Static difference-in-differences estimates, robustness to sector controls

	Log mean wage			Log mean wage floor			Log employment		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CB shock × Post	0.0482	0.0343	0.0450	0.0505	0.0542	0.0413	-0.0197	-0.0190	0.0163
	(0.0183)	(0.0236)	(0.0129)	(0.0197)	(0.0223)	(0.0150)	(0.0353)	(0.0370)	(0.0238)
Firm shock × Post	0.0173	0.0142	0.0224	-0.0026	-0.0035	-0.0021	0.0388	0.0290	0.0461
	(0.0117)	(0.0088)	(0.0094)	(0.0022)	(0.0024)	(0.0020)	(0.0176)	(0.0159)	(0.0146)
6d sector shock × Post			0.0050			-0.0025			-0.0267
			(0.0033)			(0.0026)			(0.0107)
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	7,331	7,331	7,314	7,601	7,601	7,583
Num. fixed effects	19,608	25,126	13,195	14,605	17,913	10,700	19,608	25,126	13,195
Num. observations	81,789	81,789	81,652	48,613	48,613	48,556	81,789	81,789	81,652
Adjusted R^2	0.8503	0.8528	0.8496	0.9275	0.9308	0.9249	0.8991	0.9022	0.8989

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 ("Post"). The regressions are analogous to the ones in Table 2, but changing the approach to control for local labor market effects. The economic sector categories are constructed from a granular 6-digit economic sector variable, which was created by the tax authority of Argentina and is based on ISIC, rev 4. Standard errors are clustered at the CB unit level.

Appendix Table 6: Static difference-in-differences estimates, worker-level estimates

	Log mean wage				
	(1)	(2)	(3)	(4)	(5)
CB shock × Post	0.0206	0.0134	0.0261		0.0224
	(0.0061)	(0.0093)	(0.0114)		(0.0051)
CB shock × Post × Main CB				0.0290	
				(0.0123)	
CB shock × Post × 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 2008, 2011, and 2014 The table shows estimates of the effect of CB shocks on the log mean real 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" fixed effects 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" fixed effects include interactions between all possible hiring modality indicators as of 2008 with year indicators. Standard errors are clustered at the CB unit level.

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

	Log mean wage				Log employment			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CB shock × Post	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 × Post	0.0173	0.0211	0.0172	0.0168	0.0388	0.0304	0.0385	0.0388
	(0.0117)	(0.0122)	(0.0118)	(0.0118)	(0.0176)	(0.0173)	(0.0172)	(0.0175)
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 ("Post"), varying the set of included controls. All outcomes are computed using the full set of workers in the firm-year. The regressions are analogous to the ones in Table 2, 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 8: 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 × Post	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 × Post	0.0173	0.0156	0.0153	0.0285	0.0388	0.0359	0.0351	0.0145
	(0.0117)	(0.0108)	(0.0115)	(0.0103)	(0.0176)	(0.0174)	(0.0169)	(0.0194)
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 ("Post"). The regressions are analogous to the ones in Table 2, 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 9: 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 10: 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 11: 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 12: Summary statistics of local labor markets

Variable	N	Mean	Std. Dev.	Min	Max
Unique regions	4				
Unique sectors	792				
Unique non-local CB units	322				
Unique local CB units	696				
Indicator region "Centro"	3,883	0.6140	0.4869	0.0000	1.0000
Indicator local CB unit	3,883	0.1792	0.3836	0.0000	1.0000
Indicator retail CB 0130/75	3,883	0.2122	0.4089	0.0000	1.0000
M_g	3,883	1.0000	4.0705	0.0037	177.5467
2011–2012 model estimates:					
Mean wage (2010 ARS, 000s)	3,879	3.3127	1.2163	1.0729	22.4697
Mean wage floor (2010 ARS, 000s)	3,883	2.5882	0.7335	1.3168	11.1435
Share of firms bunching	3,883	0.2394	0.1539	0.0000	0.9952
Est. minimum productivity	3,883	3.0537	0.8661	1.5162	13.8511

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.

Appendix Table 13: Effects of export 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

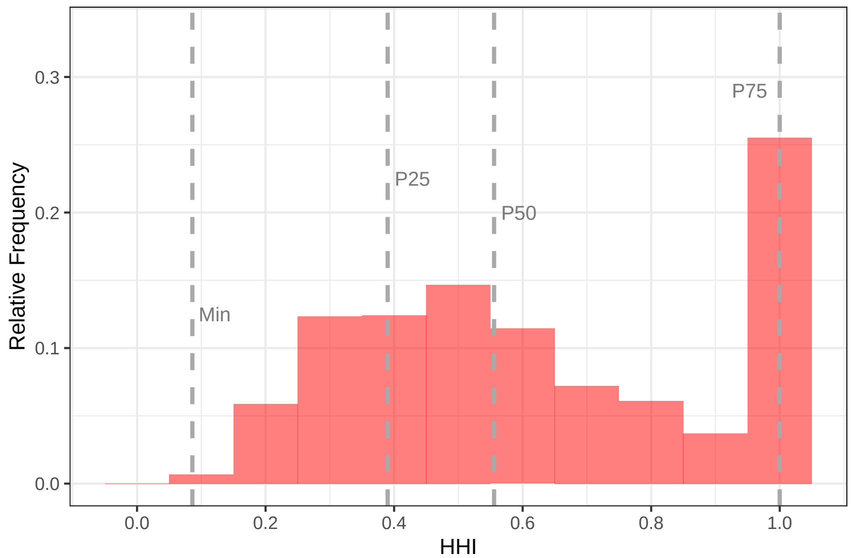
Notes: Data are from a sample of firms surveyed in the first wave of the *Encuesta Nacional de Dinámica del Empleo y la Innovación* (ENDEI). The table show estimates of export shocks on aggregate revenue at the 4-digit economic sector level on exporters and non-exporters. The baseline sample includes 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 14: 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.

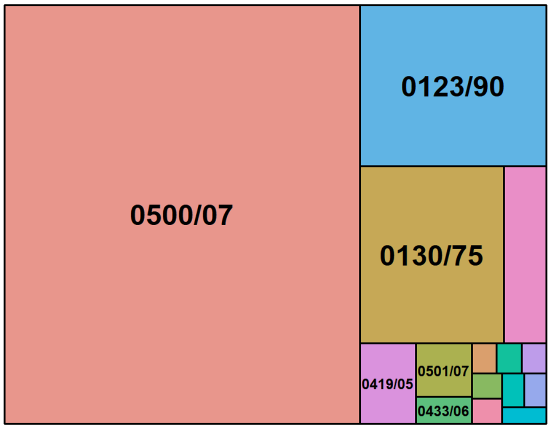
Appendix Figure 1: Concentration of employment in different CBAs within 4-digit sector and province cells



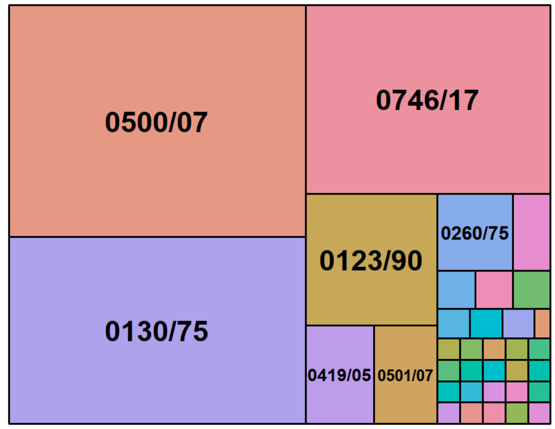
Notes: Data include all firms that had positive employment in 2012 and declared an economic sector in "Manufacturing" or "Wholesale and Retail Trade". The figure shows the distribution of the Herfindahl-Hirschman Index (HHI) of the number of firms across different CBAs within 4-digit sector and province cells. The index is computed as $HHI_\ell = \sum_c h_{c\ell}^2$, where $h_{c\ell}$ is the share of the number of firms in CBA c within the given cell ℓ, using the primary CBA code of each firm obtained by the procedure described in Appendix B.2.3.

Appendix Figure 2: Illustration of heterogeneity in coverage of CB units, textile industries

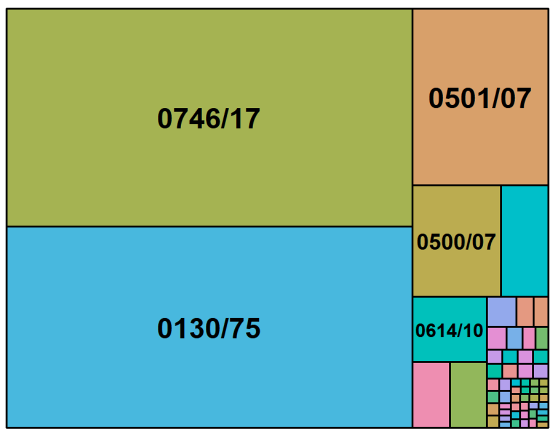
(a) Weaving of textiles



(b) Manuf. of textiles (ex. apparel)



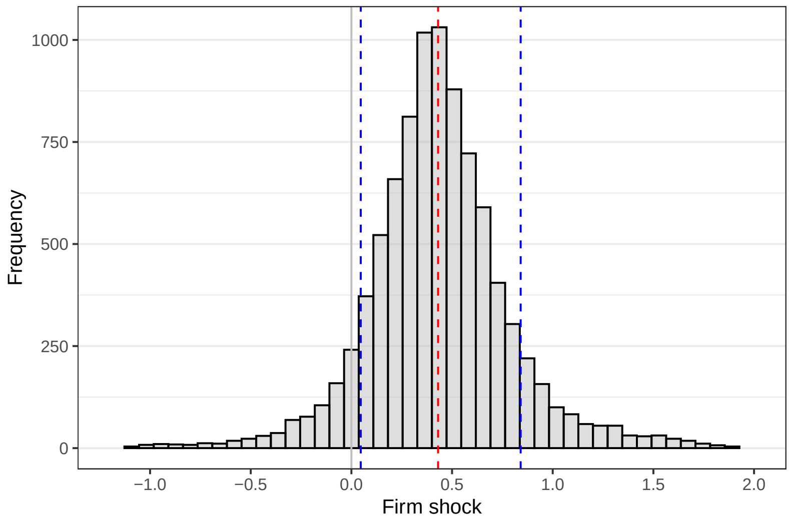
(c) Manuf. of wearing apparel (ex. fur)



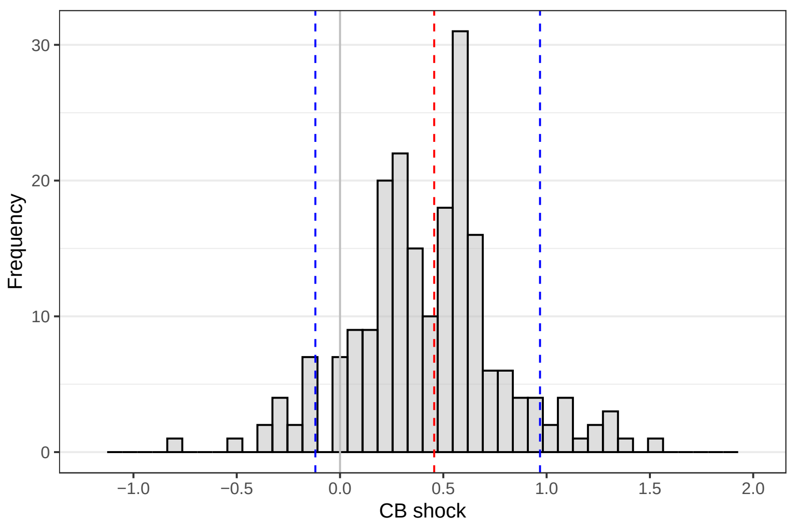
Notes: Data include all firms that had positive employment in 2012. Each box represents the sum of firms in the given economic sector, and the rectangles within each box represent the number of firms in each CB unit. The figure is based on the CB unit code of each firm obtained by the procedure described in Appendix B.2.3.

Appendix Figure 3: Distribution of export shocks

(a) Shocks to firms



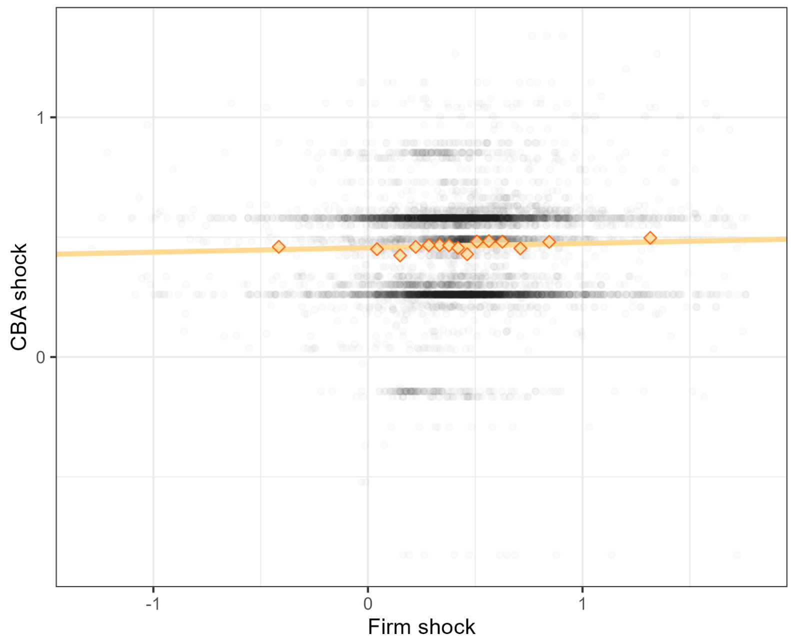
(b) Shocks to CB units



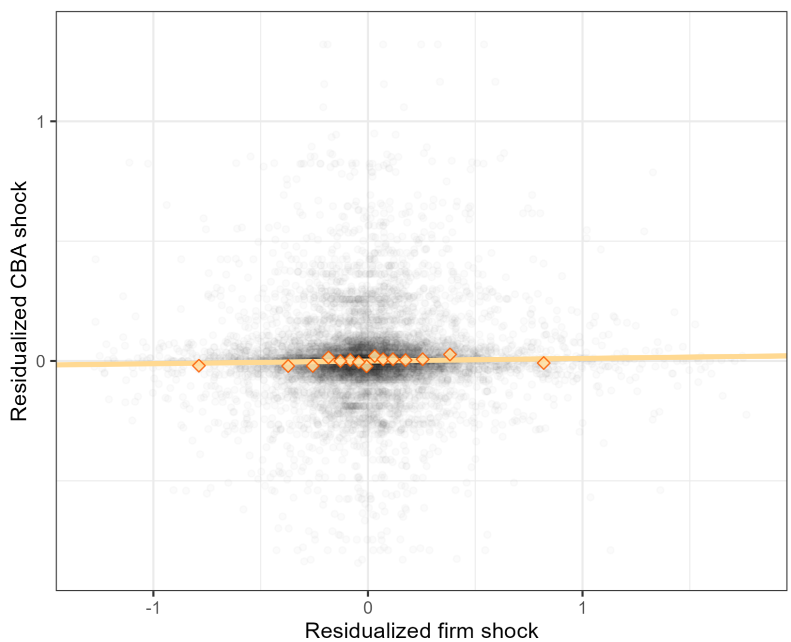
Notes: Data are constructed from a panel of firms that exported in 2011–2012. The figure illustrates the histogram of the firm and CB unit shocks. The figure excludes values lower than -1 and larger than 2 to increase visual clarity. The red dotted line in the middle shows the average shock, whereas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

Appendix Figure 4: Correlation of export shocks to firms with export shocks to CB units

(a) Raw data

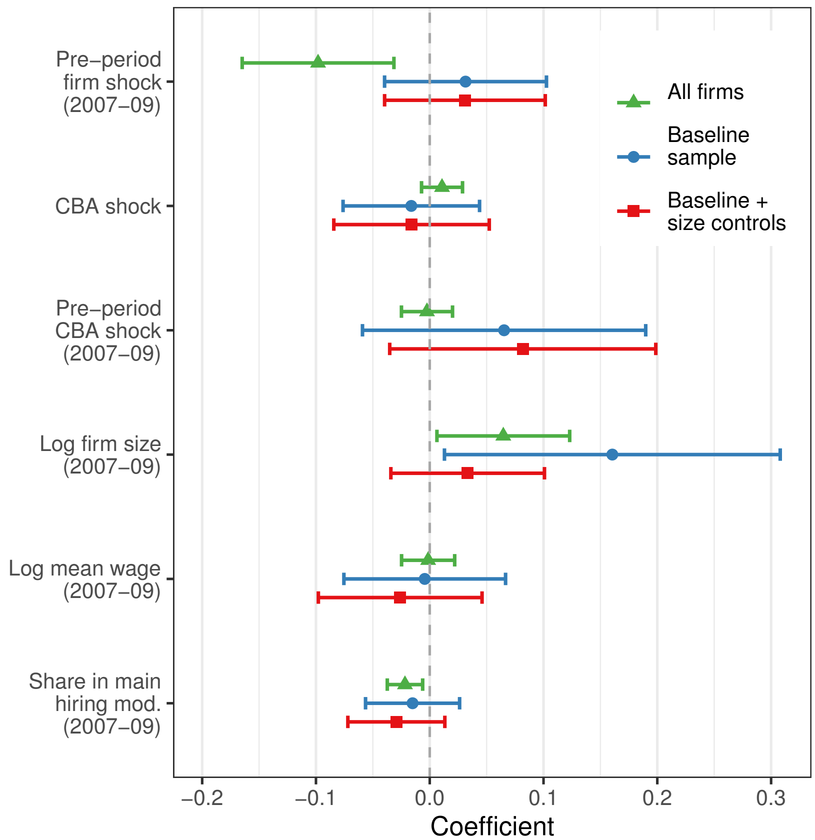


(b) Residualized on local labor market effects



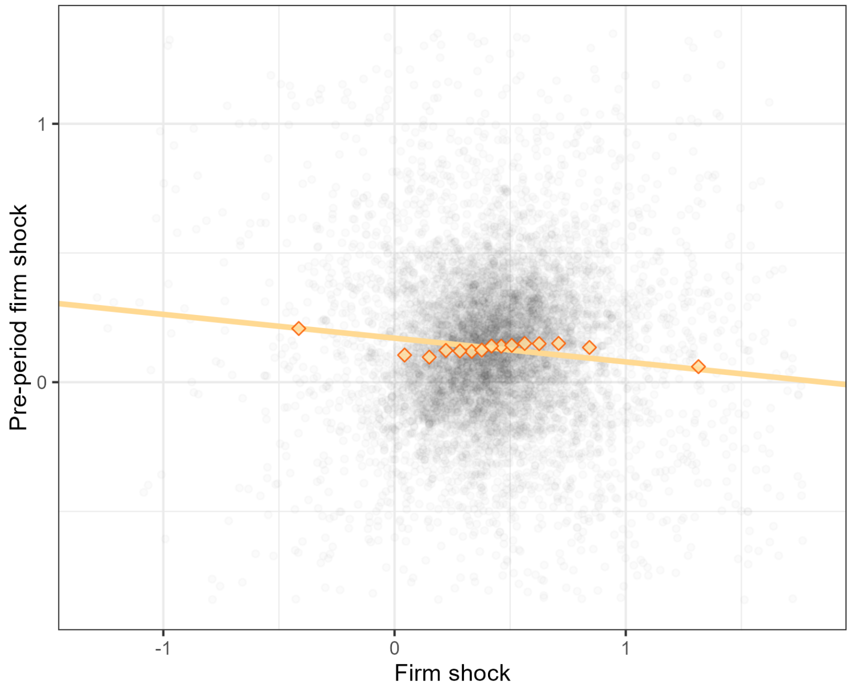
Notes: Data are constructed from a panel of firms that exported in 2011–2012. Panel (a) shows the correlation of firm shocks with CB shocks. Panel (b) shows the same correlation after residualizing for 4-digit sector by province fixed effects. The firm shock is defined as the difference between the 2012–2013 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 5: 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.

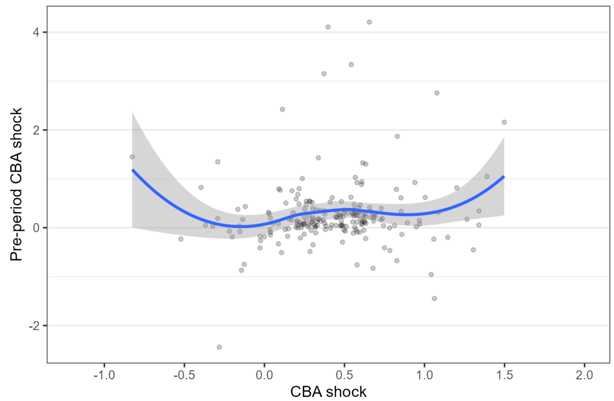
Appendix Figure 6: Auto correlation of export shocks to firms



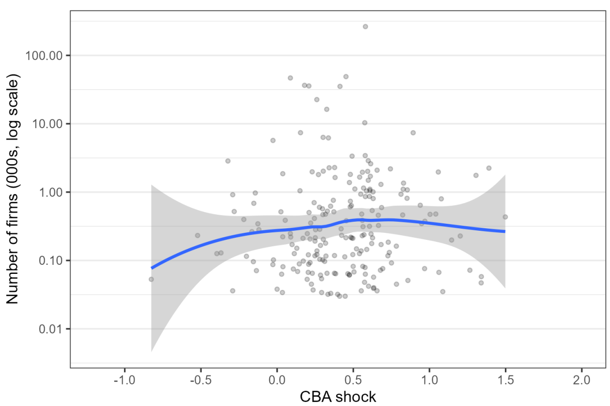
Notes: Data are constructed from a panel of firms that exported in 2011–2012. The figure shows the correlation of firm shocks, defined as the difference between the 2012–2013 average to the 2009–2010 average in the value-weighted average world import demand for the firm, with an analogous firm shock computed as the difference between 2009–2010 and 2007–2008. The red diamonds show the average firm shock within 15 bins of the pre-period firm shock. The line shows a linear fit to the data.

Appendix Figure 7: Correlates of export shocks to CB units with observables

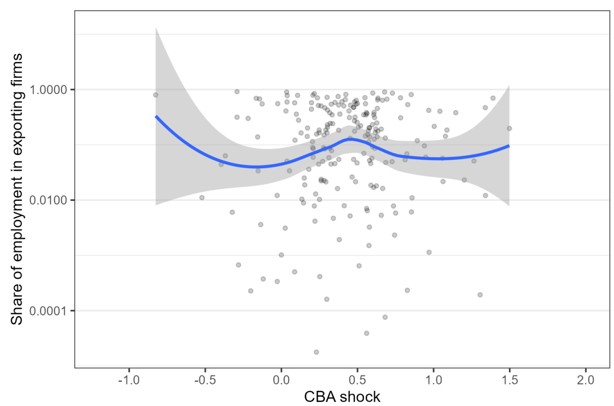
Share employment in exporting firms



Log number of firms



Share employment in exporting firms

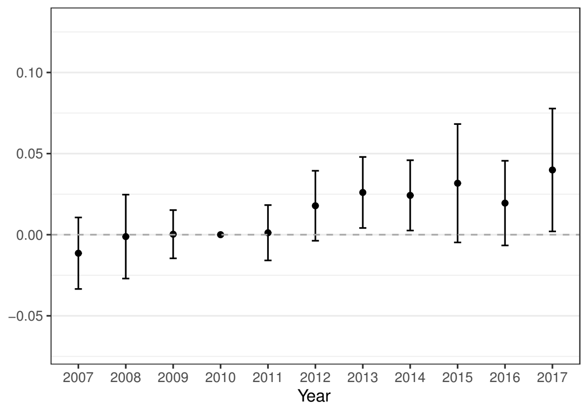


Notes: Data are constructed from a panel of firms that exported in 2011–2012. The figure shows a scatter plot of the CB unit shock with CB unit-level observables. Panel (a) uses the pre-period CB shock, constructed by differencing the proxy z_{jt} between 2008–2009 and 2008–2007. Panel (b) uses the number of firms. Panel (c) uses the share of employment in exporting firms. The line represents a locally estimated scatterplot smoothing curve fitted to the data.

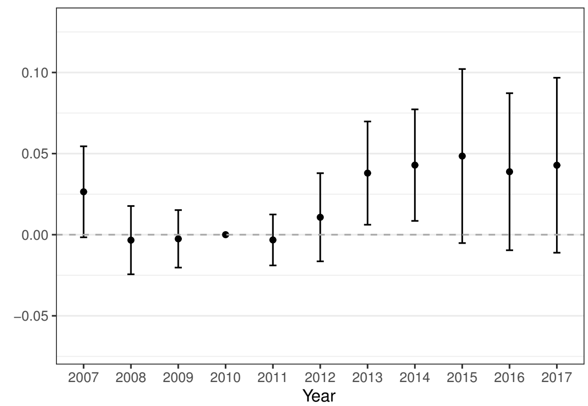
Appendix Figure 8: Effect of export shocks on mean wages and employment, excluding retail CBA

Panel (a): Log mean wages

Firm shock

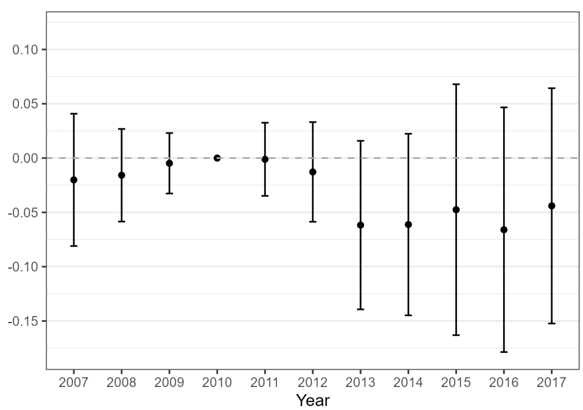


CBA shock

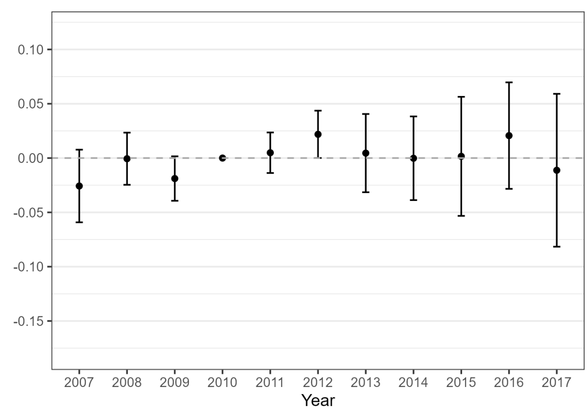


Panel (b): Log employment

CBA shock



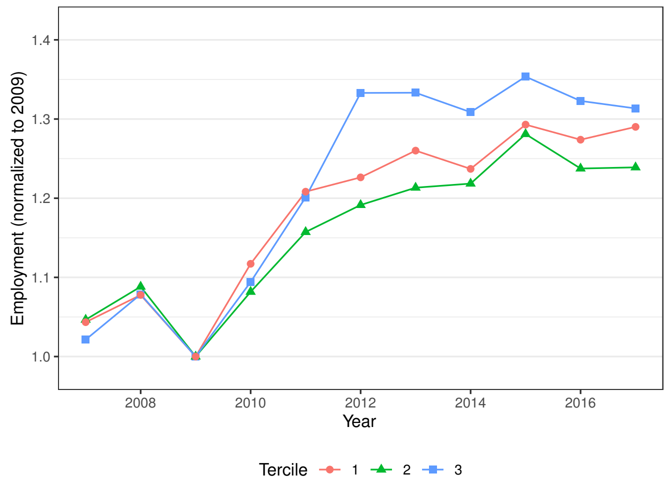
Firm shock



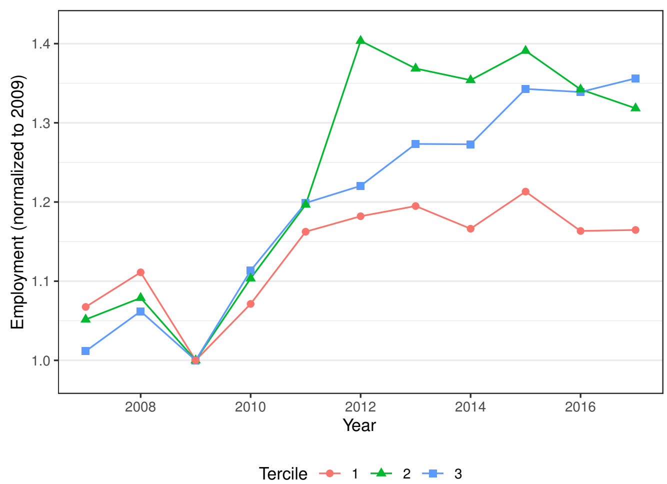
Notes: Data are from the baseline sample of exporting firms, excluding firms covered by the retail CBA 0130/75. The figure shows the dynamic effects of firm and CB shocks on log mean wages and log employment, interacting the shocks with year dummies and omitting the year 2010. The estimated models are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

Appendix Figure 9: Evolution of employment by level of CB unit and firm shock, baseline sample

(a) Shocks to firms



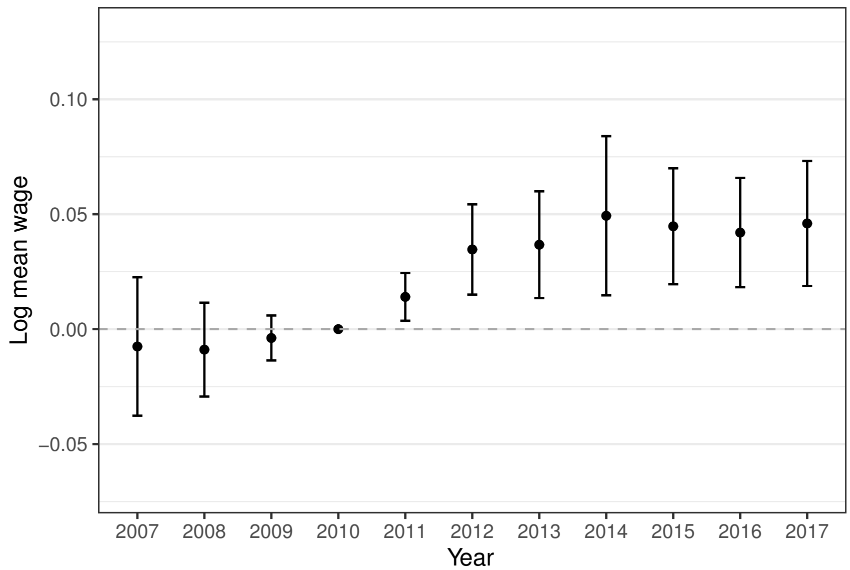
(b) Shocks to CB units



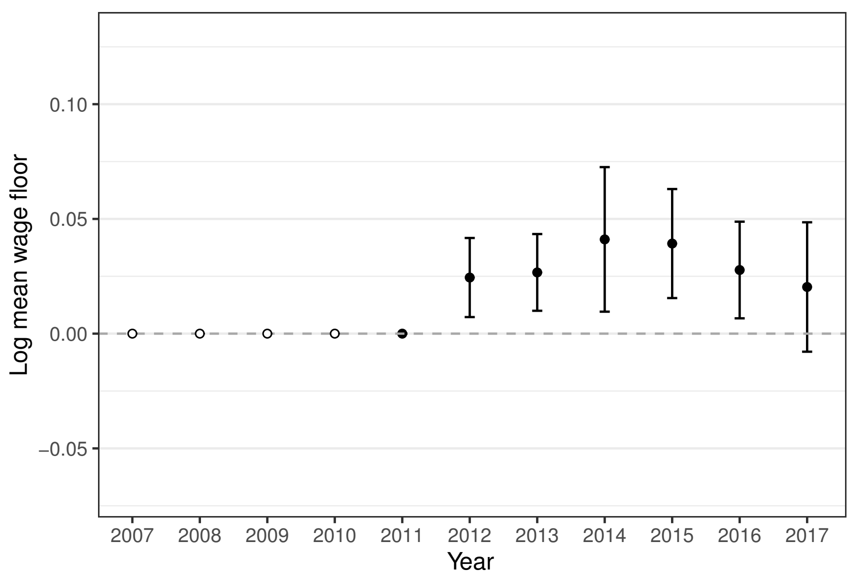
Notes: Data are from the baseline sample of exporting firms. The figure shows the average evolution of employment for firms in different terciles of the distribution of the firm shock (Panel a) and the CB shock (Panel b), relative to 2009. The firm and CB shocks are defined as the average changes in world import demand between 2009–2010 and 2012–2013, weighting by appropriate exposure shares.

Appendix Figure 10: Effect of export shocks to CB units on export and non-export firms

(a) Log mean wage

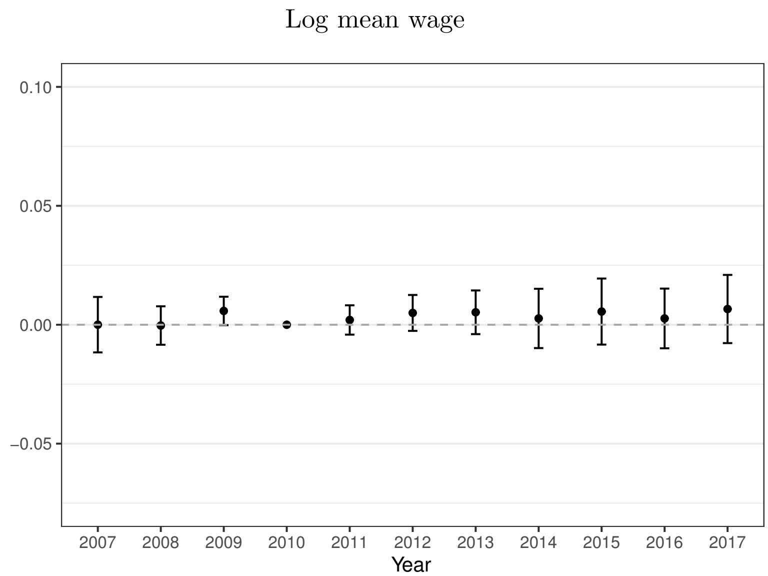


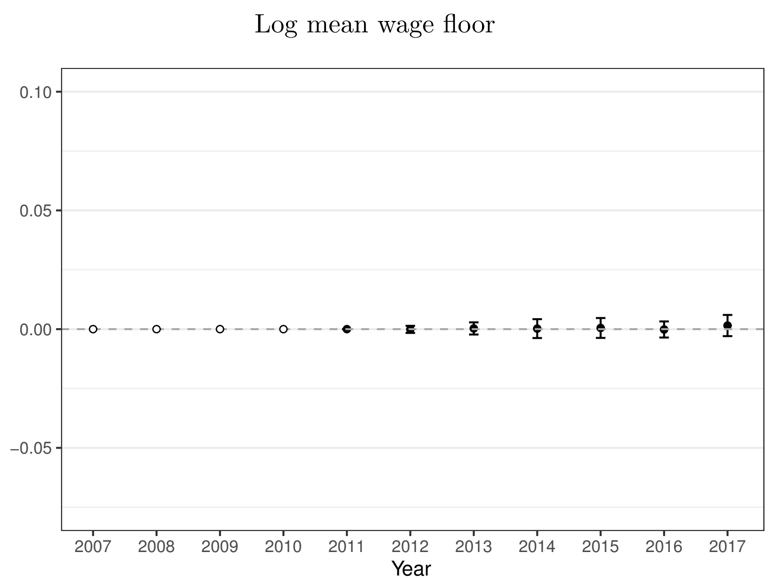
(b) Log mean wage floor



Notes: Data are from a panel of firms that are covered by an exporting CB unit in 2011–2012. The figure shows the dynamic the effects of CB shocks on mean wages and mean wage floors. The regression omits the year 2010 for the wage variable, and the year 2011 for the wage floor variable. 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 regression includes firm fixed effects, 4-digit economic sector by exporter status by province by year fixed effects, time-varying 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 and CB shocks are defined as the average changes in world import demand between 2009–2010 and 2012–2013, weighting by appropriate exposure shares. Standard errors are clustered at the CB unit level.

Appendix Figure 11: Effect of export shocks to CB units, placebo network exercise

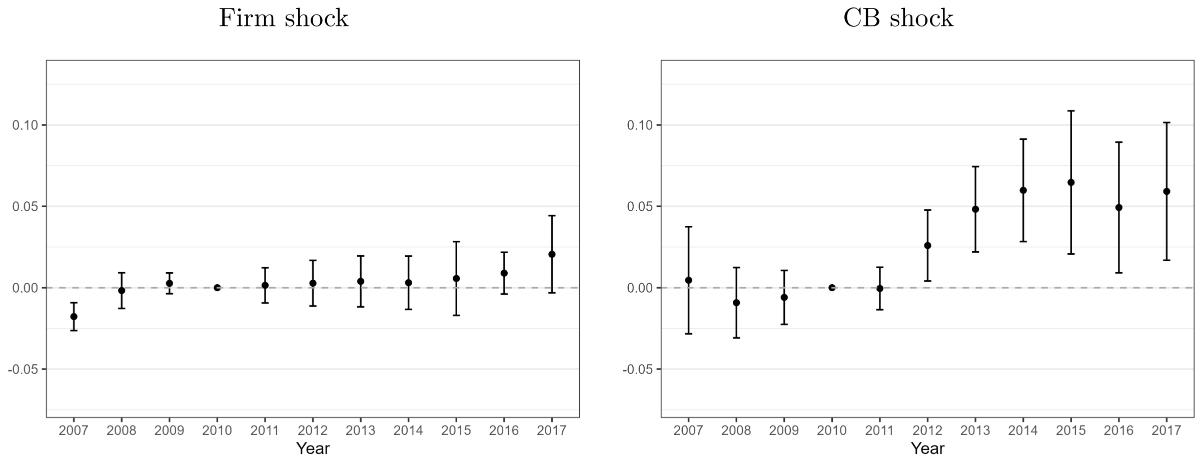




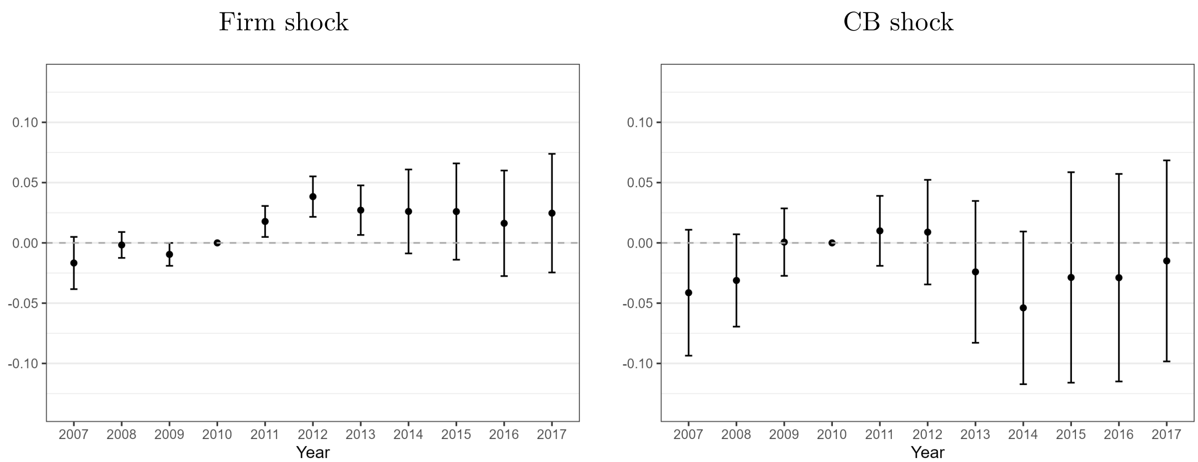
Notes: Data are from a panel of firms that exported in 2011–2012. The figure shows estimates of placebo shocks to CB units. The placebo network was constructed by randomly shifting the CB agreement code across firms within 1-digit sector and province. The top figure shows the effect of the place CB shock on log mean wages, and the bottom figure shows the effect on the log mean wage floor. The regression includes the firm shock, firm fixed effects, 4-digit economic sector by exporter status by province by year fixed effects, time-varying 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. Standard errors are clustered at the CB unit level.

Appendix Figure 12: Effect of export shocks on wages, not excluding firms with extreme values of the pre-period shock

(a) Log mean wages



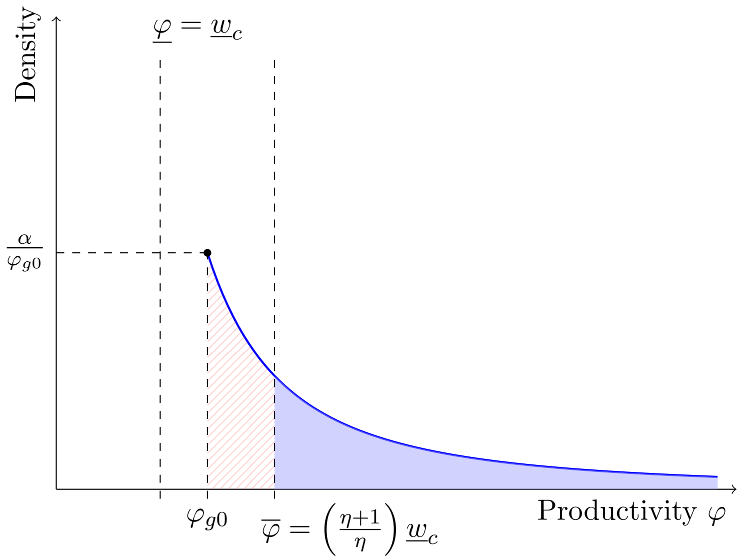
(b) Log employment



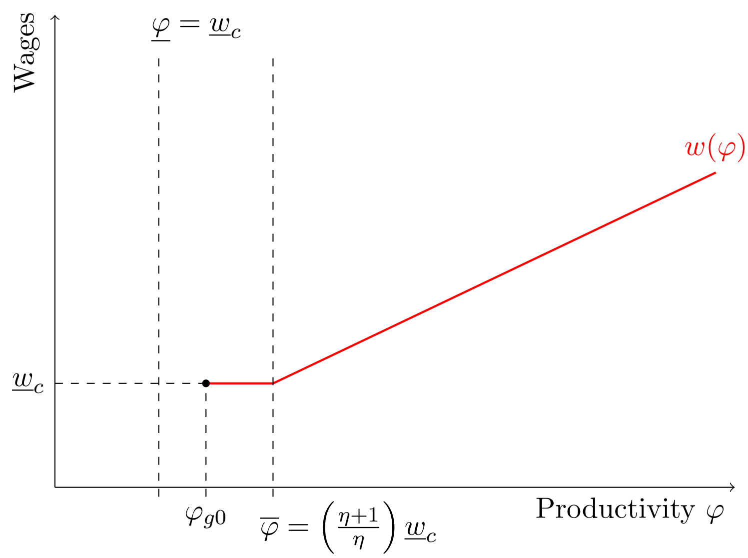
Notes: Data are from a panel of firms that are covered by an exporting CB in 2011–2012. The figure shows estimates of the effects of firm and CB shocks on log mean wages in Panel (a) and log employment in Panel (b). Estimation is done using a difference-in-differences strategy as in Figure 4 but keeping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

Appendix Figure 13: Illustration of firms productivity distribution

(a) Share of firms bunching



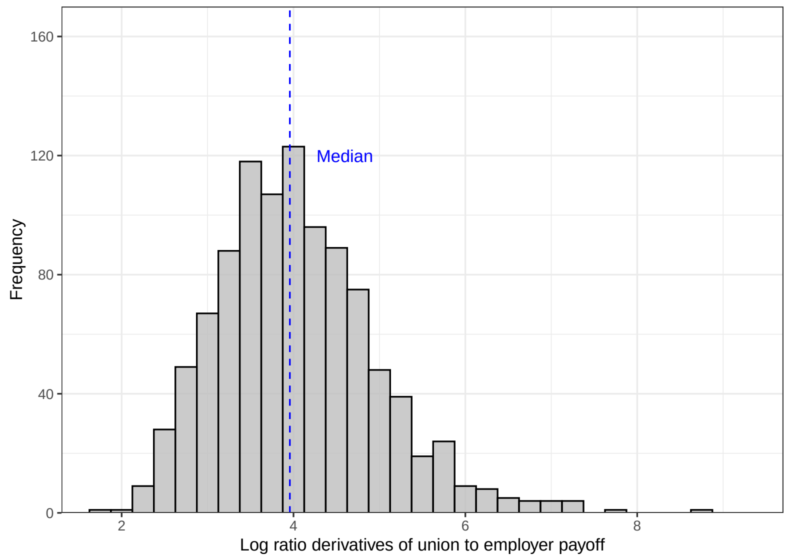
(b) Wages



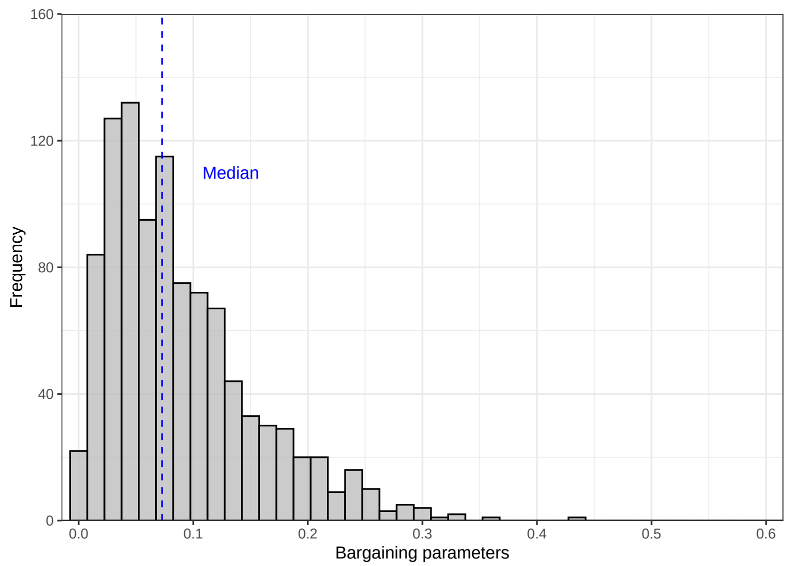
Notes: The figure illustrates the productivity distribution of firms in local labor market g with binding wage floor $\underline{w}_c$, shape productivity parameter α, and minimum value φ_{g0}.

Appendix Figure 14: Estimates of bargaining power parameters

(a) Ratio of derivatives of objective functions



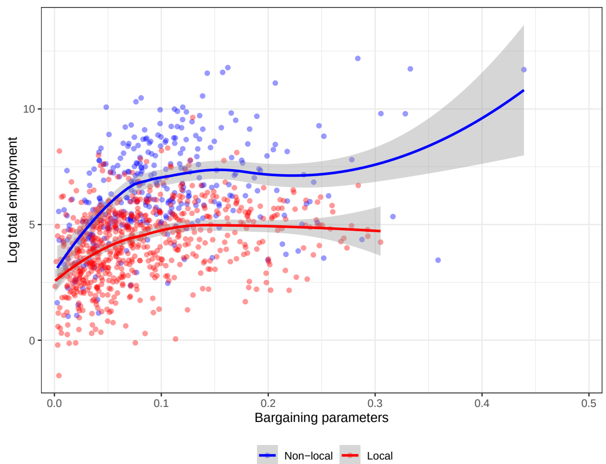
(b) Estimates of bargaining parameters



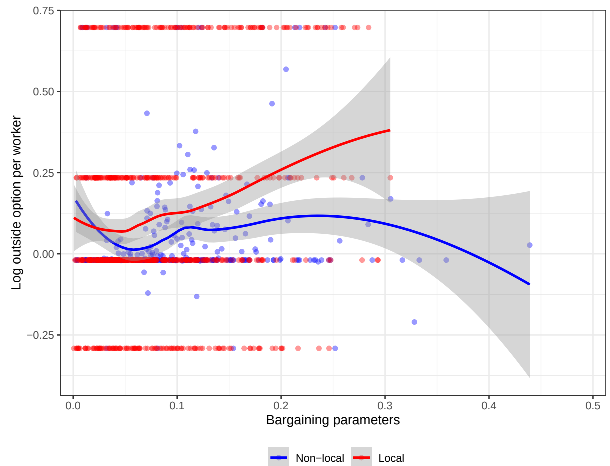
Notes: The figure shows model estimates. Panel (a) shows the estimated ratio of derivatives of the union objective function and the employer association objective function, both with respect to the wage floor. Panel (b) shows the estimated bargaining parameters. I exclude the estimates for the retail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

Appendix Figure 15: Correlations of estimated bargaining parameters with CB characteristics

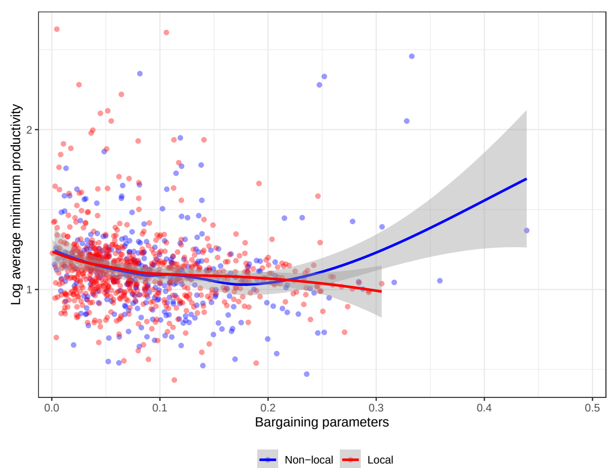
(a) Employment



(b) Outside option



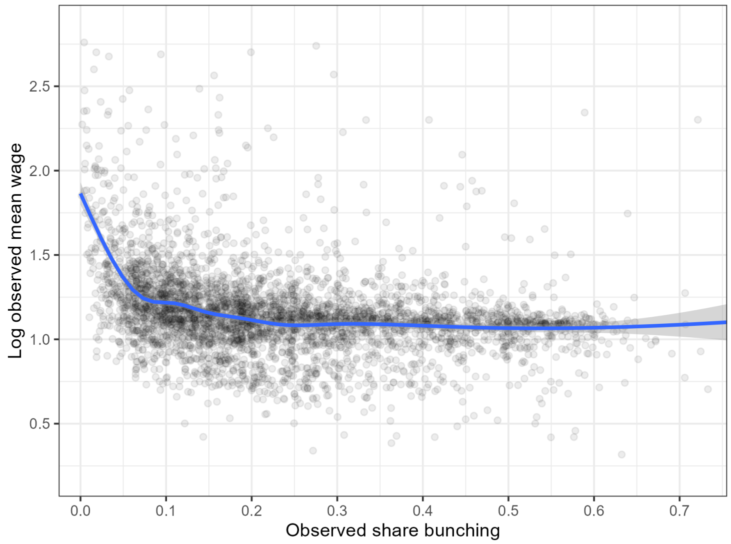
(c) Productivity



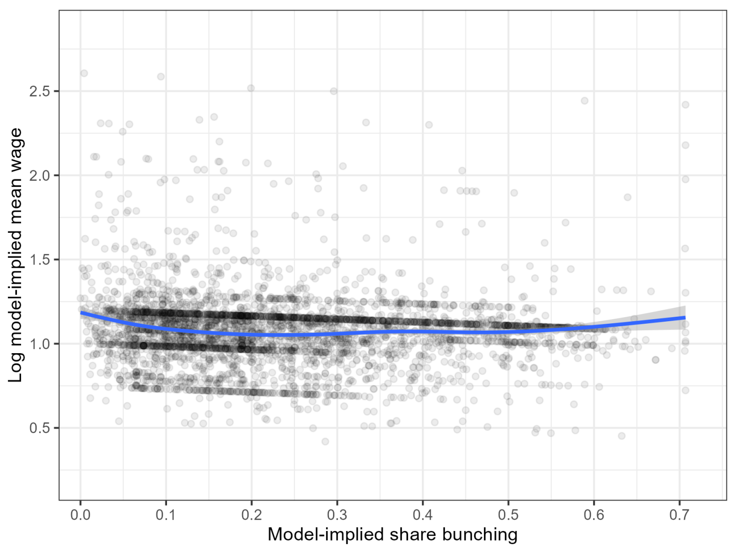
Notes: The figure shows the relationship between estimated bargaining parameters and employment (panel a), the average outside option (panel b), and the average productivity of the local labor markets it covers (panel c). The scatter is colored according to whether the CB unit is local or not. The line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

Appendix Figure 16: Share of firms bunching and mean wage in the data and in the model, for 2011–2012

(a) Data



(b) Model



Notes: The figure shows a correlation between the share of firms bunching and the mean wage in each local labor market. Panel (a) shows the data, and panel (b) shows the model-based data. The line represents a locally estimated scatterplot smoothing curve fitted to the data.