IZA Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 14390

Labor Market Power in Developing Countries: Evidence from Colombian Plants

Francesco Amodio
Nicolás de Roux

MAY 2021

DISCUSSION PAPER SERIES

IZA DP No. 14390

Labor Market Power in Developing Countries: Evidence from Colombian Plants

Francesco Amodio
McGill University, CIREQ and IZA

Nicolás de Roux
Universidad de Los Andes

MAY 2021

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

IZA DP No. 14390 MAY 2021

ABSTRACT

Labor Market Power in Developing Countries: Evidence from Colombian Plants*

How much can employers in low and middle-income countries suppress wages below marginal productivity? Using plant and customs data from Colombia, we exploit pre-determined variation across plants in sales export destination combined with variation in exchange rates to generate plant-specific shocks to marginal revenue productivity and labor demand. We estimate a firm-level labor supply elasticity of around 2.5, implying that workers produce about 40% more than their wage level. Our results indicate that Colombian and US manufacturers have a comparable degree of labor market power.

JEL Classification: J42, L10, O14, O54
Keywords: labor market power, export, Colombia

Corresponding author:
Francesco Amodio
McGill University
Leacock Building
855 Sherbrooke St. West
Montreal QC H3A 2T7
Canada
E-mail: francesco.amodio@mcgill.ca

* We thank Cristhian Acosta for excellent research assistance. We are thankful to Arin Dube, Fabian Lange, Suresh Naidu, Fernando Saltiel, Eric Verhoogen and Román David Zárate as well as conference session participants at NEUDC 2020 and SOLE 2021 for their comments. Errors remain our own. We gratefully acknowledge the Social Sciences and Humanities Research Council of Canada for financial support. All the data processing and analysis was carried in DANE's servers and in accordance with their data confidentiality guidelines.

1 Introduction

Over the last decades, the share of income going to labor has decreased in almost all the richest countries in the world (Dao et al. 2017). At the same time, industry concentration has increased steadily.[1] These two facts are interrelated. When few large firms dominate the labor market, they can afford to pay lower wages that do not match labor productivity. Recent papers show that employers in the US may enjoy a certain degree of labor market power (Benmelech et al. 2020; Azar et al. 2019, 2020; Bassier et al. 2020; Berger et al. 2021), and that the increase in market power or rise of superstar firms is one of the causes of the decline in the labor share of income (Autor et al. 2020; Barkai 2020; De Loecker et al. 2020).

Much less is known about these issues in lower-income countries. Gollin (2002) shows that the share of income going to labor is systematically lower in poor countries, but only when the labor income of the self-employed is not accounted for. This is consistent with larger firms in developing countries paying differentially lower wages. Poor countries also have high rates of informal self-employment, which affects employees' outside options and employment opportunities (Amodio et al. 2021). Moreover, labor market institutions in low and middle-income countries are typically more favorable to employers than to employees. This is especially true in Latin America, where many countries have a history of violent repression of labor market disputes and low unionization rates (Saavedra and Maruyama 1999; Mejía and Uribe 2009; Klor et al. 2020). While countries in the developing world struggle to achieve sustained economic growth, competitive labor markets are essential for allowing workers to share its benefits and lifting the poorest segment of the population out of poverty. Measuring the labor market power of employers in low-income countries is crucial for informing policies that aim to promote inclusive economic growth.

This paper uses data from Colombia to measure the degree of market power that employers have in the labor market. To measure labor market power, the labor economics literature focuses on the elasticity of the labor supply faced by the individual firm. Firms with labor market power face an upward-sloping supply curve due to a multiplicity of mechanisms that involve search frictions, firm-specific amenities, and limited geographic mobility of workers (Manning 2003, 2010; Card et al. 2018; Méndez-Chacón and Van Patten 2021). Estimating the elasticity of labor supply is challenging because wages are endogenously determined by the interaction of the supply and the demand of labor.

We overcome these identification challenges by combining plant and customs data. We merge the information from the Encuesta Anual Manufacturera (EAM) [Annual Manufacturing Survey], a census of Colombian manufacturing plants, with data on their international transactions

[1] The Next Capitalist Revolution. (2018, November 17). The Economist. Retrieved from https://goo.gl/oVyzXu.

in the period 1994 to 2009. Similar to, among others, Park et al. (2010) and Bastos et al. (2018), we leverage pre-determined variation across plants in sales export destination combined with variation in currency exchange rates to generate plant-specific shocks to the marginal revenue productivity and thus variation in labor demand.[2]

A simple model of imperfect labor market competition informs our empirical analysis. Following a positive shock to marginal revenue productivity, if the labor market is perfectly competitive, the equilibrium number of hired workers will increase, but the wage paid will not. This is because the firm takes the price of labor as given and equal to the ongoing market wage. If the firm has labor market power, both the equilibrium number of hired workers *and* the wage paid will increase. We can thus identify the elasticity of the inverse labor supply curve by taking the ratio between the log change in wage and the log change in employment.

Evidence shows that Colombian manufacturers have high labor market power. We estimate a firm-level inverse labor supply elasticity of about 0.4 implying that the marginal revenue product of labor is about 40% higher than the wage paid. This is true only for plants that account for a large share of local employment, favoring an oligopsonistic labor market framework over other possible interpretations. Our findings stand up to a battery of robustness checks including alternative sample selection and definitions of the export-driven marginal revenue product shock. In all specifications, we account for and net out shocks that affect all plants within the same metropolitan areas and narrowly defined industries, which could potentially bias the estimated labor supply elasticity at the firm level. We also show that conditioning on the full set of local labor market-sector-year fixed effects does not affect our results. Finally, we rule out the possibility that our findings are driven by changes in workforce composition or skill premium that can come with a positive export shock. We do so by estimating the labor supply elasticity using data on blue-collar workers only, for which we expect heterogeneity in skills to be less salient.

In order to identify the elasticity of labor supply faced by the individual firm, the labor economics literature has focused on specific settings such as the labor market of schoolteachers (Ransom and Sims 2010), military hospitals (Staiger et al. 2010), nurses (Matsudaira 2014), university faculty (Goolsbee and Syverson 2019), online labor markets (Dube et al. 2020), and the construction industry (Kroft et al. 2020). These papers generally find low supply elasticities and interpret this as evidence of labor market power. More recently, Azar et al. (2019) use data on job applications from the largest US employment website and find that the firm-level labor supply elasticity in the US is about 5.8. Using matched employer-employee data from

[2] Park et al. (2010) use this strategy to generate exogenous variation in the exports of Chinese firms while Bastos et al. (2018) use it to instrument for the average income of destination countries of exporting Portuguese firms. Hummels et al. (2014) and Brambilla and Porto (2016) also use exchange-rate based instruments at the firm level. More recently, de Roux et al. (2021) use import origins shares interacted with real exchange rate shocks to construct instruments for input use and estimate production function elasticities using the same plant-level data that we use in this paper.

Oregon, Bassier et al. (2020) provide new estimates of the separation elasticity implying a firm-level labor supply elasticity of 4.2, consistent with recent experimental and quasi-experimental evidence.[3] For Colombian manufacturers, we estimate an average plant-level labor supply elasticity of around 2.5 and a wage markdown of 1.4. This is in line with the findings of Hershbein et al. (2020) who focus on US manufacturers and, using a production function estimation approach, estimate an average markdown of 1.53.

Our contribution to the literature is twofold. First, we adapt the methodology of previous studies and leverage granular information on exports combined with plausibly exogenous variation in exchange rates to generate plant-specific shocks to labor demand. We use these shocks to estimate the labor market power of Colombian manufacturers. Our approach and results are complementary to the small but growing literature on labor market distortions in low-income countries. Brooks et al. (2019) find strong evidence of labor market power in Chinese and Indian manufacturing, their estimates of labor supply elasticity ranging between 0.4 and 2.5. Tortarolo and Zárate (2020) use our same data on Colombian plants to disentangle the extent of imperfect competition in product and labor markets. Using intermediate inputs as instruments for wages, they find that on average firms pay wages that are 11% lower than the marginal revenue product of labor. Using employer-employee data from Brazil, Tucker (2017) shows that firms have more monopsony power over current workers than over new hires. Pham (2019) shows that China's trade policy reforms of 2001 reduced labor market distortions while MacKenzie (2019), using plant-level data from India, shows that trade causes a larger reduction in product markups than on labor markdowns.

Second, our results speak to the literature on the effects of exporting for firms in low-income countries (Clerides et al. 1998; Atkin et al. 2017; Garcia-Marin and Voigtländer 2019) and their workers (Verhoogen 2008; Frias et al. 2012). Most recently, Frias et al. (2018) use the late-1994 devaluation of the Mexican peso to show that exporting has a significant positive effect on the wage premia of Mexican firms, and limited effects on workforce skill composition. Our findings are consistent with theirs in showing that exchange rate-driven positive export shocks increase wages. We qualify this effect further by contrasting the change in wages with the change in employment to measure the firm-level inverse labor supply elasticity and thus labor market power among Colombian firms.

The rest of the paper is organized as follows. Section 2 illustrates the simple framework that guides our analysis. Section 3 introduces the data and empirical strategy. Section 4 illustrates the main empirical results while Section 5 explores their robustness. Section 6 concludes by discussing possible alternative interpretations of our findings.

[3] See Cho (2018), Dube et al. (2020) and Kroft et al. (2020) among others.

2 Conceptual Framework

A simple, textbook model of imperfect labor market competition informs our empirical analysis (Manning 2003). Consider a firm that produces output Y using labor N as input, i.e. $Y = Y(N)$ with $Y'(N) > 0$ and $Y''(N) < 0$. Output is sold at a given exogenous price P. If the labor market is perfectly competitive, the firm faces an infinitely elastic labor supply and takes the market wage w as given. If the firm has labor market power, its supply of labor will depend on the wage offered and be equal to $N(w)$. Let $w(N)$ denote the inverse labor supply.

The firm chooses the amount of labor that maximizes

$$PY(N) - w(N)N \tag{1}$$

which leads to the first order condition

$$\begin{aligned} P\frac{\partial Y(N)}{\partial N} &= w(N) + \frac{\partial w(N)}{\partial N}N \\ P\frac{\partial Y(N)}{\partial N} &= w(N)\left[1 + \frac{\partial w(N)}{\partial N}\frac{N}{w(N)}\right] \end{aligned} \tag{2}$$

where the LHS denotes the marginal revenue product of labor (MRPL), and the RHS denotes the marginal cost of labor (MCL). This equation makes clear that the MCL and its relationship to the wage $w(N)$ are affected by the inverse elasticity of labor supply $\varepsilon = \frac{\partial w(N)}{\partial N}\frac{N}{w(N)}$.

If the labor market is perfectly competitive, then $\varepsilon = 0$, $w(N) = w$, and the MRPL equals the ongoing market wage. This situation is depicted in the left panel of Figure 1. If the firm has labor market power, the inverse labor supply curve is upward-sloping. As shown in the right panel of Figure 1, this introduces a wedge at equilibrium between the MRPL and the wage paid by the firm. The size of the wedge is a measure of labor market power and is exactly equal to ε.

Consider now the impact of a positive change in the unit price of output P. Each unit produced commands now a higher price: the MRPL curve shifts upwards. The left panel of Figure 1 shows that, if the labor market is perfectly competitive, the equilibrium number of hired workers will increase, but the wage paid will not. This is because the firm still takes the price of labor as given and equal to the ongoing market wage. This is not the case if the firm has labor market power. Both the equilibrium number of hired workers *and* the wage paid will increase, as shown in the right panel of Figure 1.

This discussion makes it clear that we can exploit exogenous changes in the MRPL to identify the elasticity of the inverse labor supply curve, which is a measure of labor market power. Under the null hypothesis of perfectly competitive labor markets, changes in the MRPL do not lead to higher wages. Under the alternative hypothesis of a firm that has some degree of labor market power, wages would change with the MRPL. We can then identify the elasticity of the inverse labor supply curve by taking the ratio between the log change in wage and the log change in employment, i.e. $\varepsilon = \frac{\Delta w}{\Delta N}\frac{N}{w} \approx \frac{\Delta log(w)}{\Delta log(N)}$.

This static framework does not contemplate any dynamics. If labor supply responds to wage changes with a lag, the firm's labor market power is a weighted average of the short-run and long-run inverse elasticity of labor supply (Boal and Ransom 1997). Even if labor supply is perfectly elastic in the long run, its short-run inverse elasticity is still informative of labor market power, the more so the higher the firm's future discount rate.

3 Empirical Strategy

Data and Exchange Rate Shocks We combine three sources of data. The first one is the Encuesta Anual Manufacturera (EAM) [Annual Manufacturing Survey].[4] Administered by Colombia's national statistical agency (DANE), the EAM is a census of all Colombian manufacturing plants with 10 or more employees. We use plant-level data from 1994 to 2009. The data provide information on plant-level quantities and prices for both outputs and inputs at fine product code levels. We use information on output to assign plants to sectors. In particular, we consider the 2, 3 and 5-digit product code the plant has produced the most in value for the sample period, and assign the plant to the corresponding sector. Importantly for our purpose, the data also carry information on the number of workers and wage bill, reported separately for blue-collar (production) and white-collar (managers and technicians) workers.

We combine this information at the plant level with transaction-level data from Colombia's customs agency, the Dirección de Impuestos y Aduanas Nacionales (DIAN). The data provide detailed information on each and all international transactions made by Colombian firms – exports and imports – including product code, transaction quantity, value, and, importantly, the destination or origin country of the transaction. We merge each plant in the EAM dataset with customs records to establish whether the firm to which each plant belongs exported or imported to a given country in a given year. Finally, we use exchange and inflation rates from the International Financial Statistics (IFS).[5]

A crucial component of our empirical analysis is the construction of exogenous firm-level shocks to the marginal revenue product of labor and thus labor demand. We construct these shocks as follows. First, we derive for each plant i the export share to destination country d in the previous year, labeled as S_{idt-1}. In our baseline exercises we consider only the top 20

[4]For other papers using these data see Eslava et al. (2010); Kugler and Verhoogen (2011); Fieler et al. (2018) among others.

[5]A few countries don't have information in the IFS. In those cases we gathered information from the corresponding central banks.

destination countries – by total export value of all Colombian firms in the sample period – and plants in the top 15 export (2-digit) sectors,[6] and compute

$$S_{idt-1} = \frac{Exp_{idt-1}}{\sum_d Exp_{idt-1}} \tag{3}$$

where Exp_{idt-1} is the total value of exports to destination country d in the previous year. We interpret S_{idt-1} as a firm-level measure of exposure to market conditions in country d. We can use these shares to generate a pre-determined firm-specific measure of exposure to exchange-rate fluctuations. Let then

$$R_{dt} = R^n_{dt} \left(\frac{CPI_{dt}}{CPI^{col}_t} \right) \tag{4}$$

be the real exchange rate between the Colombian peso and the foreign currency of country d at time t. R^n_{dt} is the nominal exchange rate – in pesos per unit of foreign currency – while CPI_{dt} is the Consumer Price Index in country d in the same year and CPI^{col}_t is the Consumer Price Index of Colombia at time t. An increase in R_{dt} corresponds to a real depreciation of the Colombian peso in relation to the foreign currency.

Finally, we combine the two variables and derive

$$E_{it} = \sum_d S_{idt-1} R_{dt} \tag{5}$$

E_{it} is plant-specific and time-varying. It captures export-driven firm-level shocks to marginal revenue productivity. Those plants that in the previous year have exported more to a given country experience a larger positive shock to their marginal revenue productivity when the Colombian peso depreciates in relation to that foreign currency. This is because each unit of output sold in the destination market brings in higher revenues in Colombian pesos.

Table 1 shows a set of summary statistics for the main variables we use in the empirical analysis. Nominal variables are in Colombian pesos of the year 2000. The median yearly sales value is 838 million, or about 400,000 dollars at the average exchange rate of 2,088 pesos per dollar in 2000. The median plant hires 26 workers – of which 17 are blue-collar – and has a monthly wage bill of 6.5 million, 5.6 going to blue-collar workers. The average plant hires 0.2% of the local workforce as measured by the total number of workers hired by plants in our data in the local labor market the plant operates in.

Specification We estimate the following regression specification

$$\ln y_{igst} = \theta_i + \lambda_{gt} + \delta_{st} + \beta_y E_{igst} + \gamma_y I_{igst} + u_{igst} \tag{6}$$

[6]We impose these restrictions to increase statistical power. Section 5 shows that results are robust to different choices of top export destinations and export sectors.

where y_{igst} is the dependent variable of interest of plant i located in local labor market g in sector s at time t. Plant fixed effects θ_i capture and net out time-invariant differences across plants. λ_{gt} and δ_{st} stand for local labor market-year and sector-year fixed effects as discussed below. Our coefficient of interest is β_y, which captures the effect on y_{igst} of firm-specific exchange rate-driven shocks to marginal revenue product of labor. The effect is causal insofar as E_{igst} is uncorrelated with the residual u_{igst}. We allow u_{igst} to be correlated across observations belonging to plants operating in the same 3-digit sector and local labor market by clustering standard errors at that level.

We consider two main dependent variables: the number of hired workers N_{igst} and the average wage w_{igst} paid by the firm. E_{igst} captures firm-specific positive shocks to the marginal revenue product of labor. Section 2 explains that, if the labor market is perfectly competitive, the equilibrium number of hired workers increases with E_{igst}, but the wage paid does not, i.e. $H_0 : \beta_N > 0, \beta_w = 0$. If the firm has labor market power, both the equilibrium number of hired workers *and* the wage paid will increase, i.e. $H_1 : \beta_N > 0, \beta_w > 0$.

The previous section also shows that we can estimate the elasticity of the inverse labor supply curve as the ratio between the two estimated coefficients, i.e. $\hat{\varepsilon} = \hat{\beta}_w / \hat{\beta}_N$.[7]

Identification Concerns A first concern with our identification strategy is that plants operating in the same local labor market may have similar export shares and therefore be exposed to the same exchange rate fluctuations. If this is the case, the estimated β would be biased as it would also capture the impact of market-level shocks. To address this concern, we control flexibly for local labor market conditions by adding as regressors the full set of local labor market-year fixed effects λ_{gt}.[8]

Similarly, if firms in the same sector have similar export shares, the impact of industry-level shocks would be nested in the estimated β. We take this into account by adding as regressors the full set of sector-year fixed effects δ_{st}, which net out both observed and unobserved sector-specific shocks that affect all plants operating in sector s at time t. We do this up to a 5-digit definition of sectors, effectively comparing firms within the same narrowly defined industry and year.[9]

[7]We assume that firms can adjust employment levels from t to $t + 1$ so that our estimates capture a long-run inverse elasticity. This is likely the case as we use year-to-year variation for identification. If this assumption fails, we would be estimating a short-run inverse elasticity, which is still informative of labor market power as discussed in Section 2.

[8]For this purpose, we define local labor markets as corresponding to the Áreas Metropolitanas [Metropolitan Areas] in Colombia as defined by DANE. The plants in the EAM belong to 13 different local labor markets.

[9]For example, the 3-digit industry code corresponding to "Paper Pulp, Paper, and Cardboard" is divided into 20 different 5-digit codes. As discussed later in Section 5, we check if our estimates are robust to the inclusion of location-sector-year fixed effects. We do so despite the limited variation left to exploit for identification. Table A.6 reports the corresponding results.

A third concern with our approach is that if plants that export more to a given country also import more from that country, exchange rate fluctuations will have an impact on firm decisions regarding production inputs. This may in turn have an independent impact on the marginal revenue product of labor. To address this concern, we follow a strategy analogous to de Roux et al. (2021) and use import shares during the previous year to derive a measure of exchange rate risk exposure on the import side that mirrors the one we derived for exports, which we label as I_{igst}.[10] We include it as additional regressors in all specifications in order to control for the effect that exchange rate shocks may have on labor inputs through imports.

More generally, E_{igst} is a Bartik-type term and its effect has a causal interpretation insofar as this variable is uncorrelated with the residual u_{igst} in equation (6). Goldsmith-Pinkham et al. (2020) show that a sufficient condition for this to be the case is that past firm-level export shares S_{idt-1} are orthogonal to the evolution of other unobserved determinants of y_{igst} over time. We explore the validity of this assumption with several robustness checks, reported in Section 5. In a related paper, Borusyak et al. (2018) show that if the average level of exposure to each one of the shocks is small and uncorrelated with the shocks themselves, then the instrument is valid. In our case, this requires that the average of lagged export shares S_{idt-1} across observations be small and uncorrelated to the real-exchange rate shocks R_{dt} in equation (4). This assumption seems plausible in our context since the export destinations of individual Colombian plants at a given point in time are unlikely to be systematically correlated with year-to-year fluctuations in the exchange rate.

4 Results

Sales and Production Value We start by showing that exchange rate-driven shocks impact sales and total value produced by the plant, thus affecting marginal revenue productivity and firm's labor demand. Table 2 presents the results obtained when estimating equation (6) having as dependent variable the log of total sales (Panel A) and the value of the plant's production (Panel B).[11] Plant fixed effects and the import shock variable I_{igst} are included as additional regressors in all specifications, while different time trends are controlled for across columns. Column (1) reports the estimates obtained when including year fixed effects while columns (2) to (5) report the estimates obtained when including local labor market-year fixed effects. Columns (3), (4) and (5) show the estimates obtained when also adding 2-digit, 3-digit and 5-digit sector-year fixed effects. Panel A shows that the effect of the exchange rate-driven export shock on sales is positive and significant in all specifications. The coefficient of column (5)

[10] Specifically, we derive $SI_{iot-1} = \frac{Imp_{iot-1}}{\sum_o Imp_{iot-1}}$ with Imp_{iot-1} being the total value of imports from origin country o in the previous year, and calculate $I_{it} = \sum_o SI_{iot-1} \ln(R_{ot})$.

[11] Both variables are measured in constant pesos of the year 2000.

implies that an increase in the export shock measure of one standard deviation is associated with a 1.3% increase in sales. Similarly, Panel B shows that export shocks lead to an increase in the value of the plant's production. The result in column (5), which accounts for 5-digit sector-specific time-varying shocks, implies that an increase in the export shock measure of one standard deviation leads to an increase of the total value produced by the plant of 1.5%.

Number of Workers and Wages Table 3 reports the estimated effect of the export shock on the number of workers hired by the plant (Panel A) and the average wage (Panel B). Each column includes a different set of fixed effects, mirroring Table 2. Panel A shows that devaluation shocks are associated with an increase in the number of workers hired by the plant. The coefficient of column (5) implies that a one standard deviation increase in the export shock measure increases the number of workers hired by 1%. At the same time, the results in Panel B show that export shocks increase the average wage paid by the plant. In all five columns the coefficient is positive and significant which implies that, even after controlling for local labor market conditions and narrowly defined industry specific shocks, positive exchange rate-driven shocks increase average wages. The coefficient of column (5) implies that a one standard deviation increase in the export shock variable increases wages by 0.4%.

Labor Supply Elasticity and Market Power Using the estimated coefficients reported in Panel A and B of Table 3 we can estimate the inverse elasticity of the labor supply curve faced by the average Colombian plant. In Section 3, we explain how the inverse elasticity is equal to $\varepsilon = \beta_w/\beta_N$. Panel C of Table 3 shows for each specification the estimated ε, equal to the coefficient from Panel B divided by the corresponding coefficient of Panel A, and its corresponding standard error. The estimated inverse elasticity ranges from 0.36 to 0.41. This last estimate implies that the marginal revenue product of labor is 41% higher than the wage paid, which is evidence that Colombian manufacturing plants have a meaningful degree of labor market power.

Panel D shows the estimated elasticity of the labor supply curve. An increase in wages of 1% leads to an increase in the supply of labor ranging from 2.44% to 2.94%. Focusing on US manufacturers, Hershbein et al. (2020) estimate an average plant-level labor supply elasticity of 1.88. Based on our estimates and corresponding standard errors, we cannot reject at standard levels of significance the null hypothesis that Colombian manufacturers have the same degree of labor market power of their US counterparts.

Heterogeneity The model of Section 2 is a simple partial equilibrium model. A general equilibrium oligopsony model of the labor market would imply that firm size relates directly to the inverse elasticity of the labor supply curve (Berger et al. 2021). In particular, whenever a plant accounts for a large share of employment in the local labor market its degree of labor market power is higher. We test this hypothesis as follows. We compute the baseline share of workers employed by the plant relative to the total number of workers employed by all plants in the local labor market the plant belongs to.[12] We then separate plants in two groups: above and below the median local labor market employment share. In Table 4, we present the estimated effect of the export shock on the number of workers and wages as obtained separately for these two subsamples. The first five columns show the results for plants with above-median local labor market employment share. The export shock has an effect on both the number of workers (Panel A) and average wages (Panel B). Columns (6) to (10) report the estimated effect for plants with below the median local labor market employment share. Here the export shock has a significant effect on the number of workers (Panel A), but the effect on wages is essentially zero (Panel B). Moreover, comparing the two sets of estimates in Panel A we notice that the effect on the number of workers is larger for firms with below-median local labor market employment share than for firms with above the median employment share, which is consistent with the labor supply curve being steeper for plants in the second group. Indeed, the estimated inverse elasticity of the labor supply curve is much lower for plants with below-median local labor market employment share than for plants with above-median employment share. These results support the hypothesis that plants that account for a large share of employment in their local labor market have higher labor market power, in line with an oligopsonistic labor market framework. Importantly, Berger et al. (2021) show that in this case the reduced-form firm-level elasticity estimated using plant-level shocks overestimates the structural elasticity. Therefore our estimate of the inverse labor supply elasticity (and hence of labor market power) is a lower bound of the structural inverse elasticity.

5 Robustness

In this section we briefly discuss several robustness checks. We report the corresponding tables in the Appendix. We start by showing that our results are robust to alternative definitions of the exchange rate-driven export shocks and estimation samples. Tables A.1 and A.2 show that the results of Table 3 are robust to the set of destination countries and export sectors considered in the construction of the export shock. We obtain similar estimates if we consider the top 100 destination countries instead of the top 20, and plants in the top 10 export sectors as opposed to the top 15 used in the baseline exercise.

Next, we investigate whether our results are robust to using different definitions of export shares. Table A.3 shows that using shares in $t-2$ instead of shares in $t-1$ does not change

[12] We compute employment shares in the first year we observe the plant in the data. Around 61% of the plants are observed in the first year of the sample, i.e. 1994.

the results. Table A.4 reports the estimates obtained when considering destination shares in the period 1994-1997 and implementing the analysis over plant observations in 1998 through 2009.[13] While somewhat less precise, the results are very similar to those reported in Table 3, and support the assumption that the shares used in the baseline version of the export shock are indeed exogenous.

To further explore the exogeneity of the shares, Table A.5 presents the results from a placebo exercise that estimates the effects of leads of the export shock on the main variables of interest. If shares are orthogonal to the evolution of the number of workers and wages through time, these leads should not have any effect on the number of workers hired by the plant or the average wage at time t. To define the leads we use leads of the exchange rates and replace them in equation (5). That is, we define E_{it+s} by substituting the term R_{dt} – the real exchange rate of destination country d in year t – in equation (5) with its lead R_{dt+s}. Table A.5 shows the estimated effect of the leads of the export shock on the number of hired workers (Panel A). In general, the leads are not correlated with wages or employment. The only exception is in Column (2), Panel B, were we find a positive and significant relation between the lead E_{it+1} and wages. Yet, this is not necessarily problematic as E_{it+1} can be serially correlated with E_{it} through serial correlation of the exchange rate terms R_{dt} and R_{dt+1}. Indeed, when we control for E_{it} in column (4), the effect of E_{it+1} on wages is no longer significant.

In Table A.6, we report the estimates we obtain when conditioning on the full set of local labor market-sector-year fixed effects. This means we exploit for identification variation in the export shock across firms within the same sector, local labor market, and year. Despite the limited residual variation, all estimates are stable across specifications and remarkably similar to the baseline ones reported in Table 3.

A final concern is that exchange rate-driven export shocks may induce changes in workforce composition or the skill premium at the firm level. A positive export shock can induce firms to upgrade the quality of their products and hire not only more workers, but also better workers that command higher wages. This would increase both the average wage paid by exporting firms, but also within-industry and within-plant wage dispersion (Verhoogen 2008; Frias et al. 2012). We address this concern by focusing on blue-collar (production) workers, for which we expect that heterogeneity in skills is less salient than for white-collar workers (managers and technicians). In doing this, we can also study the extent to which firm-level revenue productivity growth trickles down to the bottom of the working pyramid. Table A.7 shows that the effect of the export shock on the number of blue-collar workers and blue-collar wages is similar to the effect on all workers and wages. When controlling for 5-digit sector-year fixed effects in column (5), the estimated inverse elasticity of the labor supply is no longer significant, but still as high as 0.29 corresponding to an elasticity of 3.4. Finally, Table A.8 shows

[13] In this case the term S_{idt-1} of equation (3) is constant across years and is equal to the ratio between exports of plant i in years 1994-1997 to destination d and total exports of plant i in 1994-1997.

that export shocks have no impact on the share of blue collar workers, suggesting little change in workforce composition, a result consistent with Frias et al. (2018).

6 Discussion

This paper uses data on plants and their international transactions to measure the degree of labor market power among Colombian manufacturers. Plants that experience a positive, exchange-rate driven export shock hire more workers and pay higher wages, consistent with them facing an upward-sloping labor supply curve. We estimate a firm-level elasticity of labor supply of around 2.5, implying that workers produce around 40% more than their wage level.

We interpret the empirical results through the lens of a simple model of imperfect labor market competition. Yet, alternative mechanisms could explain the positive relationship we find between export shocks and wages. On the one hand, results could be consistent with a model in which workers bargain with employers over wages. But, this is unlikely to be the case in the context of Colombia, which lacks strong unions. According to household survey data, the unionization rate among manufacturing workers across metropolitan areas averages around 1%.[14] On the other hand, our findings could be consistent with an efficiency wage model where detection of shirking falls with size, and employers hiring more workers need to pay a higher wage to ensure that the no shirking condition holds (Rebitzer and Taylor 1995; Dube et al. 2018). However, this would not explain our finding that the wage-employment gradient is larger for plants that account for a large share of employment in their local labor market. If anything, workers at these plants should face less incentives to shirk given the scarcity of outside options. A final concern pertains to the role of minimum wage. Relative to the median wage, Colombia's national minimum wage is among the highest of Latin America (Mondragón-Vélez et al. 2010). The presence of a binding minimum wage drives down the estimated inverse elasticity of the labor supply (Tortarolo and Zárate 2020). This means that we are estimating a lower bound of the labor market power of Colombian plants. The questions of what determines this degree of labor market power and whether and how these results generalize to other lower-income countries motivates our future research agenda on this topic.

[14]Data from the *Gran Encuesta Integrada de Hogares*, Colombia's household survey conducted by DANE. We find an average unionization rate among manufacturing workers across metropolitan areas of 1.1% in 2008 and 0.9% in 2009.

References

Amodio, F., P. Medina, and M. Morlacco (2021). Labor market power, self-employment, and development. Mimeo.

Atkin, D., A. K. Khandelwal, and A. Osman (2017). Exporting and Firm Performance: Evidence from a Randomized Experiment. *The Quarterly Journal of Economics 132*(2), 551–615.

Autor, D., D. Dorn, L. F. Katz, C. Patterson, and J. Van Reenen (2020). The Fall of the Labor Share and the Rise of Superstar Firms*. *The Quarterly Journal of Economics 135*(2), 645–709.

Azar, J., S. Berry, and I. Marinescu (2019). Estimating labor market power. Mimeo.

Azar, J., I. Marinescu, and M. I. Steinbaum (2020). Labor market concentration. *Journal of Human Resources*, forthcoming.

Barkai, S. (2020). Declining labor and capital shares. *The Journal of Finance 75*(5), 2421–2463.

Bassier, I., A. Dube, and S. Naidu (2020). Monopsony in movers: The elasticity of labor supply to firm wage policies.

Bastos, P., J. Silva, and E. Verhoogen (2018). Export destinations and input prices. *American Economic Review 108*(2), 353–92.

Benmelech, E., N. Bergman, and H. Kim (2020). Strong employers and weak employees: How does employer concentration affect wages? *Journal of Human Resources*, forthcoming.

Berger, D. W., K. F. Herkenhoff, and S. Mongey (2021). Labor market power. Mimeo.

Boal, W. M. and M. R. Ransom (1997). Monopsony in the labor market. *Journal of Economic Literature 35*(1), 86–112.

Borusyak, K., P. Hull, and X. Jaravel (2018). Quasi-experimental shift-share research designs. NBER working paper no. 24997.

Brambilla, I. and G. G. Porto (2016). High-income export destinations, quality and wages. *Journal of International Economics 98*, 21–35.

Brooks, W. J., J. P. Kaboski, Y. A. Li, and W. Qian (2019). Exploitation of labor? classical monopsony power and labor's share. Mimeo.

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

Cho, D. (2018). The labor market effects of demand shocks: Firm-level evidence from the recovery act. Mimeo.

Clerides, S., S. Lach, and J. R. Tybout (1998). Is Learning by Exporting Important? Micro-Dynamic Evidence from Colombia, Mexico, and Morocco. *The Quarterly Journal of Economics 113*(3), 903–947.

Dao, M. C., M. Das, Z. Koczan, and W. Lian (2017). Why is labor receiving a smaller share of global income? theory and empirical evidence. Working Paper 17/169, International Monetary Fund.

De Loecker, J., J. Eeckhout, and G. Unger (2020). The Rise of Market Power and the Macroeconomic Implications*. *The Quarterly Journal of Economics 135*(2), 561–644.

de Roux, N., M. Eslava, S. Franco, and E. Verhoogen (2021). Estimating production functions in differentiated-product industries with quantity information and external instruments. NBER Working Paper 28323.

Dube, A., J. Jacobs, S. Naidu, and S. Suri (2020). Monopsony in online labor markets. *American Economic Review: Insights 2*(1), 33–46.

Dube, A., A. Manning, and S. Naidu (2018, September). Monopsony and employer mis-optimization explain why wages bunch at round numbers. Working Paper 24991, National Bureau of Economic Research.

Eslava, M., J. Haltiwanger, A. Kugler, and M. Kugler (2010). Factor adjustments after deregulation: Panel evidence from colombian plants. *The Review of Economics and Statistics 92*(2), 378–391.

Fieler, A. C., M. Eslava, and D. Y. Xu (2018). Trade, quality upgrading, and input linkages: Theory and evidence from colombia. *American Economic Review 108*(1), 109–46.

Frias, J., D. Kaplan, E. Verhoogen, and D. Alfaro-Serrano (2018). Exports and wage premia: Evidence from mexican employer-employee data. CDEP-CGEG Working Paper no. 64.

Frias, J. A., D. S. Kaplan, and E. Verhoogen (2012). Exports and Within-Plant Wage Distributions: Evidence from Mexico. *American Economic Review 102*(3), 435–440.

Garcia-Marin, A. and N. Voigtländer (2019). Exporting and plant-level efficiency gains: It's in the measure. *Journal of Political Economy 127*(4), 1777–1825.

Goldsmith-Pinkham, P., I. Sorkin, and H. Swift (2020). Bartik instruments: What, when, why, and how. *American Economic Review 110*(8), 2586–2624.

Gollin, D. (2002). Getting income shares right. *Journal of Political Economy 110*(2), 458–474.

Goolsbee, A. and C. Syverson (2019). Monopsony power in higher education: A tale of two tracks. Working Paper 26070, National Bureau of Economic Research.

Hershbein, B., C. Macaluso, and C. Yeh (2020). Monopsony in the u.s. labor market. Mimeo.

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

Klor, E. F., S. Saiegh, and S. Satyanath (2020). Cronyism in State Violence: Evidence from Labor Repression During Argentina's Last Dictatorship. *Journal of the European Economic Association*. jvaa029.

Kroft, K., Y. Luo, M. Mogstad, and B. Setzler (2020, June). Imperfect competition and rents in labor and product markets: The case of the construction industry. Working Paper 27325, National Bureau of Economic Research.

Kugler, M. and E. Verhoogen (2011). Prices, Plant Size, and Product Quality. *The Review of Economic Studies 79*(1), 307–339.

Lu, Y., Y. Sugita, and L. Zhu (2019). Wage and Markdowns and FDI Liberalization. Discussion paper series HIAS-E-83, Hitotsubashi Institute for Advanced Study, Hitotsubashi University.

MacKenzie, G. (2019). Trade and market power in product and labor markets. Mimeo.

Manning, A. (2003). *Monopsony in Motion: Imperfect Competition in Labor Markets*. Princeton University Press.

Manning, A. (2010). The plant size-place effect: agglomeration and monopsony in labour markets. *Journal of Economic Geography 10*(5), 717–744.

Matsudaira, J. D. (2014). Monopsony in the low-wage labor market? evidence from minimum nurse staffing regulations. *The Review of Economics and Statistics 96*(1), 92–102.

Mejía, D. and M. J. Uribe (2009). Is Violence Against Union Members in Colombia Systematic and Targeted? Documentos cede, Universidad de los Andes - CEDE.

Méndez-Chacón, E. and D. Van Patten (2021). Multinationals, monopsony and local development: Evidence from the united fruit company. Mimeo.

Mondragón-Vélez, C., X. Peña, D. Wills, and A. Kugler (2010). Labor market rigidities and informality in Colombia. *Economía 11*(1), 65–101.

Park, A., D. Yang, X. Shi, and Y. Jiang (2010). Exporting and firm performance: Chinese exporters and the asian financial crisis. *The Review of Economics and Statistics 92*(4), 822–842.

Pham, H. (2019). Trade reform, oligopsony, and labor market distortions: Theory and evidence. Mimeo.

Ransom, M. and D. Sims (2010). Estimating the firm's labor supply curve in a "new monopsony" framework: Schoolteachers in missouri. *Journal of Labor Economics 28*(2), 331–355.

Rebitzer, J. B. and L. J. Taylor (1995). Do labor markets provide enough short-hour jobs? an analysis of work hours and work incentives. *Economic Inquiry 33*(2), 257–273.

Saavedra, J. and E. Maruyama (1999). Los retornos a la educación ya la experiencia en el perú: 1985-1997. *Pobreza y Economía Social: Análisis de una encuesta (ENNIV-1997).*

Staiger, D., J. Spetz, and C. Phibbs (2010). Is there monopsony in the labor market? evidence from a natural experiment. *Journal of Labor Economics 28*(2), 211–236.

Tortarolo, D. and R. Zárate (2020). Imperfect competition in product and labor markets. a quantitative analysis. Mimeo.

Tucker, L. (2017). Monopsony for whom? evidence from brazilian administrative data. Mimeo.

Verhoogen, E. A. (2008). Trade, Quality Upgrading, and Wage Inequality in the Mexican Manufacturing Sector. *The Quarterly Journal of Economics 123*(2), 489–530.

Tables and Figures

Table 1: Descriptive Statistics

	Mean	St. Dev.	Min	Median	Max
Sales	6,694.8	25,847.9	0.0	837.5	842,564.6
Production value	6,911.3	26,276.9	0.0	862.7	864,096.1
Hired Workers	78.1	174.9	1	26	3,687
Hired Workers (blue-collar)	53.8	129.3	0	17	3,322
Average Wage	7.9	5.5	0.0	6.5	198.7
Average Wage (blue-collar)	6.8	5.0	0.0	5.6	321.1
Employment Share	0.00	0.01	0.00	0.00	0.23
Export Shock	1.00	0.11	0.55	1.00	1.87
Import Shock	0.99	0.10	0.55	1.00	1.87

Notes. This table present the summary statistics of the main variables used in the empirical analysis. The sample consists of plants in the top 15 2-digit export sectors in the years 1994 to 2009 and the Export and Import Shocks are constructed using information on the top 20 destination countries. The unit of observation is a plant-year. There are 44,963 observations corresponding to 5,446 plants. Nominal variables (sales, production value and wages) are in millions of Colombian Pesos of the year 2000 (the average nominal exchange rate in 2000 was 2088 pesos per dollar). Sales is the total revenue of the plant in the corresponding year, production value is the total value of production at market prices. Hired workers is the total number of workers hired by the plant. Average wage is the average wage paid to workers in the plant. Hired workers (blue-collar) and Average wage (blue collar) are the corresponding values but restricted to blue collar workers. Employment share is the ratio of the total number of workers hired by the plant relative to the total number of workers hired by all plants in the same local labor market in the first year the plant is observed. Export shock is the term E_{it} as defined by equation (5) in the text. Import Shock is the equivalent term but defined using import origin shares, as explained in footnote 10 in the text.

Table 2: Effect of Export Shock on Sales and Production Value

	(1)	(2)	(3)	(4)	(5)
	A. Log of Sales				
Export shock	0.203***	0.205***	0.202***	0.170***	0.120**
	(0.053)	(0.055)	(0.052)	(0.052)	(0.050)
Adjusted R^2	0.897	0.898	0.903	0.908	0.909
	B. Log of Production Value				
Export shock	0.211***	0.213***	0.212***	0.184***	0.137***
	(0.052)	(0.054)	(0.052)	(0.052)	(0.050)
Adjusted R^2	0.895	0.896	0.901	0.906	.907
Plant FE	✓	✓	✓	✓	✓
Year FE	✓				
Year × LLM FE		✓	✓	✓	✓
Year × 2d Sector FE			✓		
Year × 3d Sector FE				✓	
Year × 5d Sector FE					✓
Observations	44,777	44,777	44,777	44,777	44,777

Notes. * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01. This table reports the estimated effect of the Export Shock E_{it} on the log of the plant total sales (Panel A) and the log of total value of production (Panel B), following the specification of equation (6) in the text. The sample consists of plants in the top 15 2-digit export sectors and E_{it} is constructed using information on the top 20 destination countries. The coefficient estimates in each column belong to different specifications. Plant fixed effects and the import shock variable I_{it} are included as additional regressors in all specifications, while different time trends are controlled for across columns. Column (1) reports the estimates obtained when including year fixed effects while columns (2) to (5) report the estimates obtained when including local labor market-year fixed effects. Columns (3), (4) and (5) show the estimates obtained when also adding 2-digit, 3-digit and 5-digit sector-year fixed effects. Standard errors clustered at the level of each local labor market × 3-digit sector are reported in parentheses.

Table 3: Effect of Export Shock on Number of Workers and Wages

	(1)	(2)	(3)	(4)	(5)
	A. Log Number of Workers				
Export shock	0.126***	0.124***	0.123***	0.115***	0.090**
	(0.034)	(0.035)	(0.036)	(0.036)	(0.038)
Adjusted R^2	0.919	0.919	0.920	0.922	0.922
	B. Log Average Wage				
Export shock	0.045***	0.045***	0.042***	0.040***	0.037***
	(0.015)	(0.013)	(0.011)	(0.011)	(0.012)
Adjusted R^2	0.810	0.811	0.826	0.829	0.833
	C. Inverse Elasticity of Labor Supply				
Inverse Elasticity	0.361***	0.362***	0.340**	0.347**	0.410**
	(0.138)	(0.139)	(0.135)	(0.144)	(0.202)
	D. Elasticity of Labor Supply				
Elasticity	2.773***	2.764***	2.941**	2.885**	2.439**
	(1.057)	(1.058)	(1.166)	(1.201)	(1.203)
Plant FE	✓	✓	✓	✓	✓
Year FE	✓				
Year × LLM FE		✓	✓	✓	✓
Year × 2d Sector FE			✓		
Year × 3d Sector FE				✓	
Year × 5d Sector FE					✓
Observations	44,963	44,963	44,963	44,963	44,963

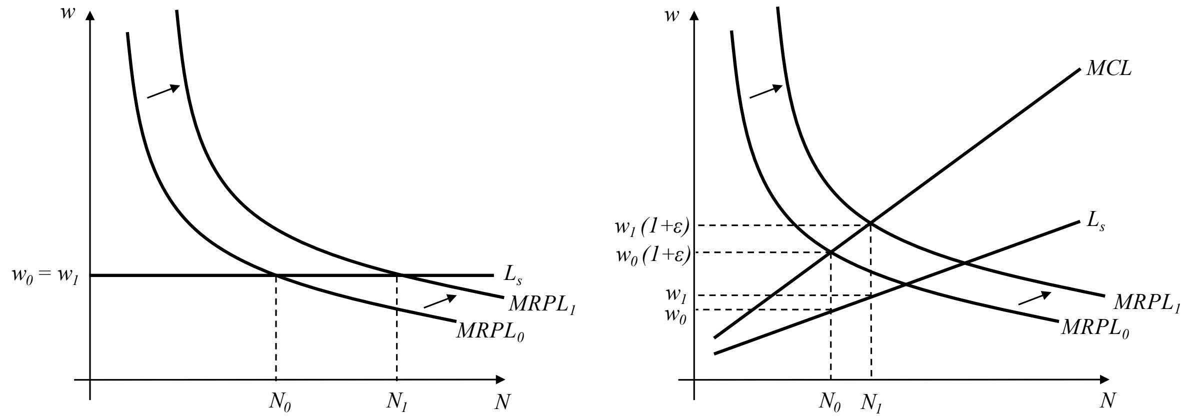
Notes. * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01. This table reports the estimated effect of the Export Shock E_{it} on the log of the number of workers hired by the plant (Panel A) and on the log of the average wage paid by the plant (Panel B), following the specification of equation (6) in the text. The sample consists of plants in the top 15 2-digit export sectors and E_{it} is constructed using information on the top 20 destination countries. The coefficient estimates in each column belong to different specifications. Plant fixed effects and the import shock variable I_{it} are included as additional regressors in all specifications, while different time trends are controlled for across columns. Column (1) reports the estimates obtained when including year fixed effects while columns (2) to (5) report the estimates obtained when including local labor market-year fixed effects. Columns (3), (4) and (5) show the estimates obtained when also adding 2-digit, 3-digit and 5-digit sector-year fixed effects. Standard errors clustered at the level of each local labor market × 3-digit sector are reported in parentheses. Panel C presents estimates of the inverse elasticity of the labor supply curve ϵ, which is obtained by dividing the coefficient in Panel B by the coefficient in Panel A, and their standard errors. Panel D reports estimates of the labor supply curve elasticity (ϵ^{-1}) and their standard error.

Table 4: Effect of Export Shock on Number of Workers and Wages
Heterogeneity According to Local Labor Market Employment Share

	Above Median Empl. Share					*Below Median Empl. Share*				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	A. Log Number of Workers									
Export shock	0.113***	0.119***	0.126***	0.120***	0.090**	0.162**	0.164**	0.145**	0.159**	0.167**
	(0.035)	(0.036)	(0.038)	(0.038)	(0.038)	(0.062)	(0.063)	(0.059)	(0.066)	(0.078)
Adjusted R^2	0.919	0.919	0.921	0.922	0.922	0.795	0.796	0.800	0.802	0.804
	B. Log Average Wage									
Export shock	0.043**	0.043**	0.041***	0.036**	0.031*	-0.013	-0.012	-0.008	-0.006	-0.001
	(0.021)	(0.018)	(0.015)	(0.016)	(0.016)	(0.024)	(0.024)	(0.026)	(0.028)	(0.033)
Adjusted R^2	0.843	0.845	0.859	0.864	0.866	0.709	0.710	0.729	0.729	0.736
	C. Inverse Elasticity of Labor Supply									
Inverse Elasticity	0.383**	0.361**	0.329**	0.285	0.343	-0.080	-0.074	-0.053	-0.037	-0.009
	(0.186)	(0.171)	(0.156)	(0.160)	(0.226)	(0.190)	(0.186)	(0.196)	(0.183)	(0.171)
	D. Elasticity of Labor Supply									
Elasticity	2.609**	2.770**	3.040**	3.352*	2.914	-12.5	-13.6	-18.7	-27.3	-112.7
	(1.265)	(1.313)	(1.445)	(1.796)	(1.915)	(29.8)	(34.4)	(68.8)	(136.0)	(2,173.1)
Plant FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓					✓				
Year × LLM FE		✓	✓	✓	✓		✓	✓	✓	✓
Year × 2d Sector FE			✓					✓		
Year × 3d Sector FE				✓					✓	
Year × 5d Sector FE					✓					✓
Observations	25,685	25,685	25,685	25,685	25,685	17,924	17,924	17,924	17,924	17,924

Notes. * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01. This table reports the estimated effect of the Export Shock E_{it} on the log of the number of workers hired by the plant (Panel A) and on the log of the average wage paid by the plant (Panel B), following the specification of equation (6) in the text. E_{it} is constructed using information on the top 20 destination countries. The sample in Columns (1) to (5) consists of plants in the top 15 2-digit export sectors and with a local labor market employment share above the median across the sample of plants. The local labor market employment share is defined as the number of workers hired by the plant dived by the total number of workers hired by all plants in the same local labor market in the first year the plant is observed. Columns (6) to (10) consider plants below the median local labor market employment share. The coefficient estimates in each column belong to different specifications. Plant fixed effects and the import shock variable I_{it} are included as additional regressors in all specifications, while different time trends are controlled for across columns. Column (1) and (6) report the estimates obtained when including year fixed effects while columns (2) to (5) and (6) to (10) report the estimates obtained when including local labor market-year fixed effects. Columns (3), (4) and (5) and (8), (9) and (10) show the estimates obtained when also adding 2-digit, 3-digit and 5-digit sector-year fixed effects. Standard errors clustered at the level of each local labor market × 3-digit sector are reported in parentheses. Panel C presents estimates of the inverse elasticity of the labor supply curve ϵ, which is obtained by dividing the coefficient in Panel B by the coefficient in Panel A, and their standard errors. Panel D reports estimates of the labor supply curve elasticity (ϵ^{-1}) and their standard error.

Figure 1: Textbook Model of Imperfect Labor Market Competition



Notes: The Figures illustrate the equilibrium number of hired workers and wages if the labor market is perfectly competitive – left panel – and if the firm has some labor market power – right panel. If this is the case, a wedge exists at equilibrium between the MRPL (equal to the MCL) and the wage paid by the firm. The size of the wedge is exactly equal to the inverse labor supply elasticity ε. The Figures also show how the equilibrium changes following a positive change in the unit price of output P, which amounts to the MRPL curve shifting upwards. If the labor market is perfectly competitive, the equilibrium number of hired workers will increase, but the wage paid will not. If the firm has some labor market power, both the equilibrium number of hired workers *and* the wage paid will increase.

A Appendix: Additional Tables

Table A.1: Effect of Export Shock on Number of Workers and Wages
Top 100 Destinations

	(1)	(2)	(3)	(4)	(5)
	A. Log Number of Workers				
Export shock	0.140***	0.138***	0.138***	0.129***	0.103***
	(0.034)	(0.034)	(0.036)	(0.036)	(0.038)
Adjusted R^2	0.919	0.919	0.920	0.922	0.922
	B. Log Average Wage				
Export shock	0.049***	0.049***	0.045***	0.042***	0.041***
	(0.014)	(0.013)	(0.011)	(0.011)	(0.012)
Adjusted R^2	0.810	0.811	0.826	0.829	0.833
	C. Inverse Elasticity of Labor Supply				
Inverse Elasticity	0.354***	0.352***	0.329***	0.325**	0.401**
	(0.124)	(0.125)	(0.119)	(0.127)	(0.173)
	D. Elasticity of Labor Supply				
Elasticity	2.826***	2.838***	3.041***	3.073**	2.496**
	(0.993)	(1.005)	(1.101)	(1.198)	(1.077)
Plant FE	✓	✓	✓	✓	✓
Year FE	✓				
Year × LLM FE		✓	✓	✓	✓
Year × 2d Sector FE			✓		
Year × 3d Sector FE				✓	
Year × 5d Sector FE					✓
Observations	44,963	44,963	44,963	44,963	44,963

Notes. * p-value $<$ 0.1; ** p-value $<$ 0.05; *** p-value $<$ 0.01. This table reports the estimated effect of the Export Shock E_{it} on the log of the number of workers hired by the plant (Panel A) and on the log of the average wage paid by the plant (Panel B), following the specification of equation (6) in the text. The sample consists of plants in the top 15 2-digit export sectors and E_{it} is constructed using information on the top 100 destination countries. The coefficient estimates in each column belong to different specifications. Plant fixed effects and the import shock variable I_{it} are included as additional regressors in all specifications, while different time trends are controlled for across columns. Column (1) reports the estimates obtained when including year fixed effects while columns (2) to (5) report the estimates obtained when including local labor market-year fixed effects. Columns (3), (4) and (5) show the estimates obtained when also adding 2-digit, 3-digit and 5-digit sector-year fixed effects. Standard errors clustered at the level of each local labor market $\times$ 3-digit sector are reported in parentheses. Panel C presents estimates of the inverse elasticity of the labor supply curve ϵ, which is obtained by dividing the coefficient in Panel B by the coefficient in Panel A, and their standard errors. Panel D reports estimates of the labor supply curve elasticity (ϵ^{-1}) and their standard error.

Table A.2: Effect of Export Shock on Number of Workers and Wages
Top 10 Export Sectors

	(1)	(2)	(3)	(4)	(5)
	A. Log Number of Workers				
Export shock	0.140***	0.139***	0.136***	0.129***	0.098**
	(0.038)	(0.039)	(0.041)	(0.040)	(0.045)
Adjusted R^2	0.920	0.920	0.921	0.922	0.922
	B. Log Average Wage				
Export shock	0.055***	0.052***	0.044***	0.044***	0.043***
	(0.016)	(0.014)	(0.012)	(0.012)	(0.014)
Adjusted R^2	0.825	0.826	0.838	0.841	0.846
	C. Inverse Elasticity of Labor Supply				
Inverse Elasticity	0.389***	0.376**	0.325**	0.338**	0.436**
	(0.151)	(0.150)	(0.144)	(0.153)	(0.222)
	D. Elasticity of Labor Supply				
Elasticity	2.571***	2.662**	3.072**	2.956**	2.292**
	(0.995)	(1.061)	(1.355)	(1.334)	(1.164)
Plant FE	✓	✓	✓	✓	✓
Year FE	✓				
Year × LLM FE		✓	✓	✓	✓
Year × 2d Sector FE			✓		
Year × 3d Sector FE				✓	
Year × 5d Sector FE					✓
Observations	29,989	29,989	29,989	29,989	29,989

Notes. * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01. This table reports the estimated effect of the Export Shock E_{it} on the log of the number of workers hired by the plant (Panel A) and on the log of the average wage paid by the plant (Panel B), following the specification of equation (6) in the text. The sample consists of plants in the top 10 2-digit export sectors and E_{it} is constructed using information on the top 20 destination countries. The coefficient estimates in each column belong to different specifications. Plant fixed effects and the import shock variable I_{it} are included as additional regressors in all specifications, while different time trends are controlled for across columns. Column (1) reports the estimates obtained when including year fixed effects while columns (2) to (5) report the estimates obtained when including local labor market-year fixed effects. Columns (3), (4) and (5) show the estimates obtained when also adding 2-digit, 3-digit and 5-digit sector-year fixed effects. Standard errors clustered at the level of each local labor market × 3-digit sector are reported in parentheses. Panel C presents estimates of the inverse elasticity of the labor supply curve ϵ, which is obtained by dividing the coefficient in Panel B by the coefficient in Panel A, and their standard errors. Panel D reports estimates of the labor supply curve elasticity (ϵ^{-1}) and their standard error.

Table A.3: Effect of Export Shock on Number of Workers and Wages
Export Shares in $t-2$

	(1)	(2)	(3)	(4)	(5)
	A. Log Number of Workers				
Export shock	0.118***	0.116***	0.112***	0.108***	0.074**
	(0.032)	(0.032)	(0.033)	(0.034)	(0.036)
Adjusted R^2	0.925	0.926	0.926	0.928	0.928
	B. Log Average Wage				
Export shock	0.041***	0.041***	0.045***	0.043***	0.039***
	(0.015)	(0.013)	(0.011)	(0.012)	(0.014)
Adjusted R^2	0.816	0.817	0.832	0.835	0.838
	C. Inverse Elasticity of Labor Supply				
Inverse Elasticity	0.345**	0.352**	0.403**	0.398**	0.524*
	(0.157)	(0.160)	(0.168)	(0.174)	(0.293)
	D. Elasticity of Labor Supply				
Elasticity	2.902**	2.842**	2.480**	2.512**	1.909*
	(1.323)	(1.296)	(1.035)	(1.098)	(1.069)
Plant FE	✓	✓	✓	✓	✓
Year FE	✓				
Year × LLM FE		✓	✓	✓	✓
Year × 2d Sector FE			✓		
Year × 3d Sector FE				✓	
Year × 5d Sector FE					✓
Observations	38,873	38,873	38,873	38,873	38,873

Notes. * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01. This table reports the estimated effect of the Export Shock E_{it} on the log of the plant total sales (Panel A) and on the log of the total value of production (Panel B), following the specification of equation (6) in the text. The Export Shocks term E_{it} is constructed following equation (5) but using destination shares computed in $t-2$ instead of shares in $t-1$. The sample consists of plants in the top 15 2-digit export sectors and E_{it} is constructed using information on the top 20 destination countries. The coefficient estimates in each column belong to different specifications. Plant fixed effects and the import shock variable I_{it} are included as additional regressors in all specifications, while different time trends are controlled for across columns. Column (1) reports the estimates obtained when including year fixed effects while columns (2) to (5) report the estimates obtained when including local labor market-year fixed effects. Columns (3), (4) and (5) show the estimates obtained when also adding 2-digit, 3-digit and 5-digit sector-year fixed effects. Standard errors clustered at the level of each local labor market × 3-digit sector are reported in parentheses. Panel C presents estimates of the inverse elasticity of the labor supply curve ϵ, which is obtained by dividing the coefficient in Panel B by the coefficient in Panel A, and their standard errors. Panel D reports estimates of the labor supply curve elasticity (ϵ^{-1}) and their standard error.

Table A.4: Effect of Export Shock on Number of Workers and Wages
Export Shares 1994-97

	(1)	(2)	(3)	(4)	(5))
			A. Log Number of Workers		
Export shock	0.101**	0.101*	0.092*	0.087*	0.082
	(0.050)	(0.052)	(0.054)	(0.052)	(0.051)
Adjusted R^2	0.930	0.930	0.931	0.932	0.933
			B. Log Average Wage		
Export shock	0.037*	0.037**	0.049***	0.045***	0.031*
	(0.019)	(0.019)	(0.016)	(0.016)	(0.017)
Adjusted R^2	0.824	0.825	0.841	0.845	0.850
			C. Inverse Elasticity of Labor Supply		
Inverse Elasticity	0.370	0.365	0.527*	0.514	0.377
	(0.251)	(0.252)	(0.305)	(0.324)	(0.306)
			D. Elasticity of Labor Supply		
Elasticity	2.702	2.736	1.897*	1.944	2.652
	(1.835)	(1.890)	(1.098)	(1.223)	(2.154)
Plant FE	✓	✓	✓	✓	✓
Year FE	✓				
Year × LLM FE		✓	✓	✓	✓
Year × 2d Sector FE			✓		
Year × 3d Sector FE				✓	
Year × 5d Sector FE					✓
Observations	31,211	31,211	31,211	31,211	31,211

Notes. * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01. This table reports the estimated effect of the Export Shock E_{it} on the log of the plant total sales (Panel A) and on the log of the total value of production (Panel B), following the specification of equation (6) in the text. The Export Shocks term E_{it} is constructed following equation (5) but using destination shares equal total exports of the firms to the destination in years 1994-1997 divided by total exports to all destinations in the same years. The sample consists of plants in the top 15 2-digit export sectors and E_{it} is constructed using information on the top 20 destination countries. The coefficient estimates in each column belong to different specifications. Plant fixed effects and the import shock variable I_{it} are included as additional regressors in all specifications, while different time trends are controlled for across columns. Column (1) reports the estimates obtained when including year fixed effects while columns (2) to (5) report the estimates obtained when including local labor market-year fixed effects. Columns (3), (4) and (5) show the estimates obtained when also adding 2-digit, 3-digit and 5-digit sector-year fixed effects. Standard errors clustered at the level of each local labor market × 3-digit sector are reported in parentheses. Panel C presents estimates of the inverse elasticity of the labor supply curve ϵ, which is obtained by dividing the coefficient in Panel B by the coefficient in Panel A, and their standard errors. Panel D reports estimates of the labor supply curve elasticity (ϵ^{-1}) and their standard error.

Table A.5: Effect of Export Shock on Number of Workers and Wages
Leads of Export Shock

	A. Log Number of Workers				
	(1)	(2)	(3)	(4)	(5)
Export shock$_{it}$	0.087**			0.176**	0.121***
	(0.039)			(0.056)	(0.046)
Export shock$_{it+1}$		0.046		-0.108**	
		(0.036)		(0.046)	
Export shock$_{it+2}$			0.015		-0.060
			(0.032)		(0.037)
Adjusted R^2	0.935	0.935	0.935	0.935	0.935
	B. Log Average Wage				
Export shock$_{it}$	0.033**			0.024	0.032**
	(0.013)			(0.020)	(0.014)
Export shock$_{it+1}$		0.032**		0.011	
		(0.015)		(0.023)	
Export shock$_{it+2}$			0.021		0.002
			(0.015)		(0.016)
Adjusted R^2	0.861	0.861	0.861	0.861	0.861
Plant FE	✓	✓	✓	✓	✓
Year × LLM FE	✓	✓	✓	✓	✓
Year × 5d Sector FE	✓	✓	✓	✓	✓
Observations	33,935	33,935	33,935	33,935	33,935

Notes. * p-value $<$ 0.1; ** p-value $<$ 0.05; *** p-value $<$ 0.01. This table reports the estimated effect of the Export Shock E_{it} and its leads E_{it+1} and E_{it+2} on the log of the number of workers hired by the plant (Panel A) and on the log of the average wage paid by the plant (Panel B), following the specification of equation (6) in the text. Leads of the Export Shock term are obtained by substituting leads in $t+1$ and $t+2$ of the real exchange rate terms for R_{dt} in equation (5). The sample consists of plants in the top 15 2-digit export sectors and E_{it} is constructed using information on the top 20 destination countries. The coefficient estimates in each column belong to different specifications. Plant fixed effects, local labor market-year, 5-digit sector year fixed effects and the import shock variable I_{it} are included as additional regressors in all specifications. Standard errors clustered at the level of each local labor market × 3-digit sector are reported in parentheses.

Table A.6: Effect of Export Shock on Number of Workers and Wages
LLM-Sector-Year FEs

	(1)	(2)	(3)	(4)
	A. Log Number of Workers			
Export shock	0.126***	0.126***	0.120***	0.092**
	(0.034)	(0.036)	(0.036)	(0.039)
Adjusted R^2	0.919	0.920	0.921	0.922
	B. Log Average Wage			
Export shock	0.045***	0.043***	0.042***	0.039***
	(0.015)	(0.011)	(0.011)	(0.012)
Adjusted R^2	0.810	0.826	0.829	0.832
	C. Inverse Elasticity of Labor Supply			
Inverse Elasticity	0.361***	0.344***	0.352***	0.423***
	(0.115)	(0.098)	(0.096)	(0.155)
	D. Elasticity of Labor Supply			
Elasticity	2.773***	2.904***	2.838***	2.364***
	(0.881)	(0.823)	(0.771)	(0.867)
Plant FE	✓	✓	✓	✓
Year FE	✓			
Year × LLM FE × 2d Sector		✓		
Year × LLM FE × 3d Sector			✓	
Year × LLM FE × 5d Sector				✓
Observations	44,963	44,963	44,963	44,963

Notes. * p-value $<$ 0.1; ** p-value $<$ 0.05; *** p-value $<$ 0.01. This table reports the estimated effect of the Export Shock E_{it} on the log of the number of workers hired by the plant (Panel A) and on the log of the average wage paid by the plant (Panel B), following the specification of equation (6) in the text. The sample consists of plants in the top 15 2-digit export sectors and E_{it} is constructed using information on the top 20 destination countries. The coefficient estimates in each column belong to different specifications. Plant fixed effects and the import shock variable I_{it} are included as additional regressors in all specifications, while different time trends are controlled for across columns. Column (1) reports the estimates obtained when including year fixed effects. Columns (2), (3) and (4) show the estimates obtained when including local labor market-sector-year fixed effects, with the sector definition being 2-digit, 3-digit and 5-digit respectively. Standard errors clustered at the level of each local labor market × 3-digit sector are reported in parentheses. Panel C presents estimates of the inverse elasticity of the labor supply curve ϵ, which is obtained by dividing the coefficient in Panel B by the coefficient in Panel A, and their standard errors. Panel D reports estimates of the labor supply curve elasticity (ϵ^{-1}) and their standard error.

Table A.7: Effect of Export Shock on Number of Workers and Wages
Blue Collar Workers

	(1)	(2)	(3)	(4)	(5)
	A. Log Number of Workers				
Export shock	0.113***	0.111***	0.112***	0.104**	0.080*
	(0.040)	(0.040)	(0.041)	(0.042)	(0.047)
Adjusted R^2	0.903	0.903	0.905	0.906	0.907
	B. Log Average Wage				
Export shock	0.046***	0.047***	0.039**	0.037**	0.023
	(0.016)	(0.016)	(0.015)	(0.014)	(0.015)
Adjusted R^2	0.726	0.727	0.745	0.749	0.753
	C. Inverse Elasticity of Labor Supply				
Inverse Elasticity	0.408**	0.426**	0.349**	0.350*	0.293
	(0.188)	(0.195)	(0.175)	(0.189)	(0.243)
	D. Elasticity of Labor Supply				
Elasticity	2.451**	2.350**	2.868**	2.855*	3.418
	(1.130)	(1.075)	(1.441)	(1.544)	(2.834)
Plant FE	✓	✓	✓	✓	✓
Year FE	✓				
Year × LLM FE		✓	✓	✓	✓
Year × 2d Sector FE			✓		
Year × 3d Sector FE				✓	
Year × 5d Sector FE					✓
Observations	44,204	44,204	44,204	44,204	44,204

Notes. * p-value $<$ 0.1; ** p-value $<$ 0.05; *** p-value $<$ 0.01. This table reports the estimated effect of the Export Shock E_{it} on the log of the number of blue collar workers hired by the plant (Panel A) and on the log of the average wage paid by the plant to blue collar workers (Panel B), following the specification of equation (6) in the text. The sample consists of plants in the top 15 2-digit export sectors and E_{it} is constructed using information on the top 20 destination countries. The coefficient estimates in each column belong to different specifications. Plant fixed effects and the import shock variable I_{it} are included as additional regressors in all specifications, while different time trends are controlled for across columns. Column (1) reports the estimates obtained when including year fixed effects while columns (2) to (5) report the estimates obtained when including local labor market-year fixed effects. Columns (3), (4) and (5) show the estimates obtained when also adding 2-digit, 3-digit and 5-digit sector-year fixed effects. Standard errors clustered at the level of each local labor market × 3-digit sector are reported in parentheses. Panel C presents estimates of the inverse elasticity of the labor supply curve ϵ, which is obtained by dividing the coefficient in Panel B by the coefficient in Panel A, and their standard errors. Panel D reports estimates of the labor supply curve elasticity (ϵ^{-1}) and their standard error.

Table A.8: Effect of Export Shock on Share of Blue Collar Workers

	A. Share of blue collar workers				
	(1)	(2)	(3)	(4)	(5)
Export shock	-0.002	-0.003	-0.001	-0.002	-0.003
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Adjusted R^2	0.733	0.734	0.736	0.736	0.737
Plant FE	✓	✓	✓	✓	✓
Year FE	✓				
Year $\times$ LLM FE		✓	✓	✓	✓
Year $\times$ 2d Sector FE			✓		
Year $\times$ 3d Sector FE				✓	
Year $\times$ 5d Sector FE					✓
Observations	44,963	44,963	44,963	44,963	44,963

Notes. * p-value < 0.1; ** p-value < 0.05; *** p-value < 0.01. This table reports the estimated effect of the Export Shock E_{it} on the log of the number of blue collar workers hired by the plant (Panel A) and on the log of the average wage paid by the plant to blue collar workers (Panel B), following the specification of equation (6) in the text. The sample consists of plants in the top 15 2-digit export sectors and E_{it} is constructed using information on the top 20 destination countries. The coefficient estimates in each column belong to different specifications. Plant fixed effects and the import shock variable I_{it} are included as additional regressors in all specifications, while different time trends are controlled for across columns. Column (1) reports the estimates obtained when including year fixed effects while columns (2) to (5) report the estimates obtained when including local labor market-year fixed effects. Columns (3), (4) and (5) show the estimates obtained when also adding 2-digit, 3-digit and 5-digit sector-year fixed effects. Standard errors clustered at the level of each local labor market $\times$ 3-digit sector are reported in parentheses.