The Rise of China and Labor Market Adjustments in Latin America

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Abstract

This paper assesses the impact of the rise of China on the trade of Latin American and Caribbean economies. The study proposes an index to measure the impact on trade, which suggests sizable effects, especially in Argentina, Brazil, Chile, Honduras, Mexico, and Paraguay. The paper uses the index and a model of labor mobility, to calculate the impact of China’s growth on labor markets in Argentina, Brazil, and Mexico. The resulting evidence suggests that the rise of China has had positive effects on agriculture and mining in Argentina and Brazil, which offset negative impacts on manufacturing industries, thus leaving total employment and real wages virtually unchanged in the long run. In contrast, the estimated impacts of China’s rise on Mexico imply that the sizable shock to manufacturing was not offset by the positive shocks on mining and agriculture, reducing employment in the long run. The paper also discusses the effect of China on the degree of informality in these three economies and contrasts short-run and long-run effects on employment and wages across industries.

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The Rise of China and Labor Market Adjustments in Latin America *

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1 Introduction

In recent decades China has experienced impressive growth. Over the last three decades GDP growth averaged 10% per year, and over 500 million people have moved out of poverty. China is now the world’s largest exporter, manufacturer and a substantial importer of raw materials\(^1\). The value of Chinese trade has practically doubled every four years in the last three decades\(^2\). Along with this impressive growth, there has been an increasing academic and policy debate about the effects of China on other countries’ performance, particularly in Latin America \(^3\). A cacophony of voices have been heard in the media discussing the economic and social impacts of the rise of China, with some arguing about the benefits while others are more skeptical\(^4\).

For Latin American countries, several questions regarding the growth of China remain unanswered. For instance, how much of the change in net exports and prices can be attributed to the growth of China? Did China’s growth affect relative wages, employment and informality in Latin America? How difficult was it for workers to move from a sector that received a negative shock to a sector that received a positive shock? This paper contributes to the debate providing some answers. More specifically, we conceptualize China’s growth as a negative trade shock for manufacturing exporters and a positive shock for mining and agricultural exporters. Then, we identify the size of these shocks for a large set of Latin American and Caribbean economies. Finally, using the identified shocks and a structural model of labor markets, we analyze the impact on wages and employment in three large countries: Argentina, Brazil and Mexico.

From the perspective of Latin American producers, the export and import growth of China was realized as a shift in aggregate demand faced by exporters. The size and direction of these

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\(^1\)See World Bank and Development Research Center of the State Council (2013).
\(^2\)See Feenstra and Wei (2009).
\(^3\)See for example Lora (2007) and Lederman et al (2009).
shifts probably varied across countries and sectors. For example, Latin American manufacturing exporters probably faced lower prices and increased competition as China increased its market share in world markets. On the other hand, the increase of Chinese raw material imports probably contributed to the recent increase in commodity prices. As world manufacturing prices decreased, workers employed in manufacturing sectors faced downward pressures on their wages, forcing some of them to leave their sectors of employment. Unlike the manufacturing sector, as raw material prices increased, wages and employment in mining and agricultural sectors might have risen. These effects vary across countries and across sectors within a country. Moreover, the final effect on wages and employment depends on both the size of the shocks and the size of each sector as well as the costs workers face when moving between sectors of employment.

In the absence of reliable estimates of the impact of China on product-level prices, we develop vulnerability and opportunity indices for manufacturing, mining and agriculture. The objective of these indexes is to quantify the impact of China on each sector’s trade balance in a large sample of Latin American economies. Put differently, these indices give us the size of country-specific trade shocks that can be attributed to China’s increasing weight in world trade. In turn, we estimate (and partially calibrate) a neoclassical small open economy model with labor market adjustment costs using Argentine, Brazilian and Mexican data. Finally, we bring these two pieces together: We shock and calibrate the model using the vulnerability and opportunity indexes to calculate the effects of China’s export growth on wages, labor allocations, and informal employment.

The vulnerability and opportunity indexes show the potential effect of China on Latin American exports. For instance, the results suggest that China’s increased demand for mining products could have increased Brazil’s exports (of these goods) by 33% between 2001 and 2011, while Chile’s exports of mining products could have increased by 26%. Sizable increases in agricultural exports are expected for countries like Paraguay, Argentina, Uruguay and Brazil. Moreover, China’s competition in manufacturing could have significant effects on countries exporting textiles like Honduras, El Salvador and Haiti as well as countries exporting a more
diverse set of manufacturing products like Mexico.

After calculating the size of positive and negative shocks that can be attributed to China via the indices, we estimate and simulate a neoclassical small open economy model similar to Arias et al (2013). The model is also related to Artuç, Chaudhuri and McLaren’s (2010) labor mobility model but with a special emphasis on informal employment (which is especially important for Latin American economies). The model is empirically tractable, requiring only worker employment transitions across industries and employment status from labor-force surveys with panel data, which are available for Argentina, Brazil and Mexico. With these estimates of labor mobility costs, we simulate the effect of changes in labor demand across sectors to study labor-market adjustments caused by the growth of Chinese exports in global markets.

The estimation of labor mobility costs, as in Arias et al (2013), highlights three common features in the labor markets of Argentina, Brazil and Mexico. First, it is less costly to become formal if the worker stays in the same industry. Second, the highest entry costs involve moving from informal to formal and changing the sector of employment. Third, the lowest entry costs are associated with movements from formal to informal within sectors. Moreover, in the three countries the highest mobility cost is found for workers moving out of informality into formality while changing sector towards agriculture or mining. This will limit the movement of workers to these sectors which were precisely the sectors that were positively affected by China. These high switching costs thus limited the reduction of informal employment of the positive shocks emanating from China.

From the simulations we conclude that, for Argentina and Brazil, the positive shocks in agriculture and mining offset the negative shock in manufacturing leaving the total level of employment and real wages almost at the same level. In these two countries, a larger positive shock in mining and agriculture is needed to offset a smaller shock in manufacturing because this sector employs a larger proportion of workers. In Mexico, the larger shock in manufacturing provokes a reduction of employment in the long run.

The export vulnerability index we introduce herein is closely related to the studies by
Lass and Weiss (2004), Hanson and Robertson (2009) and Freund and Ozden (2009). Lall and Weiss (2004) compare Latin American and Chinese exports, product by product at the 3-digit SITC level and identify categories where China is gaining market share at the expense of Latin America between 1990 and 2002. They find that in 1990, 30% of trade was in industries where Chinese exports were increasing and Latin American exports were decreasing. On the other hand, they find that China’s threat has been decreasing gradually: By 2002, only 11% of Latin American exports seemed to be negatively affected by China. They conclude that, over time Latin American export structures became relatively complementary to China’s exports.

Similarly, Freund and Ozden (2009) find that China’s export growth had only a small negative effect on overall Latin American exports. They show that China was affecting Mexico’s industrial exports negatively, but for the rest of Latin America, they did not find any significant impact. For Mexico, they found that a 10% increase in China’s industrial exports reduced Mexico’s industrial export growth by 7.9%. Moreover, they conclude that China’s continuing export growth might be affecting the wage distribution since it is concentrated in high wage industries.

Hanson and Robertson (2009) analyzed the effect of China’s export growth on Latin America using a gravity model, where exporters produce differentiated goods and compete with Chinese exporters under monopolistic competition. First, they estimate the changes in exporter fixed effects associated with export growth. Then, they simulate a counter-factual scenario for Latin America’s manufacturing export growth setting China’s export growth rate to zero. They find that China impeded growth of manufacturing exports in Argentina by 1.1%, Brazil by 1.4%, Chile by 2.3%, and Mexico by 3.1%.

Autor, Dorn and Hanson (2013) studied the implications of the rise of China on local labor markets (defined as “Commuting Zones”) within the United States through imports of Chinese goods. The authors argue that changes in Chinese imports by other high-income countries (used as an “instrumental variable”) caused higher unemployment, reduced labor-force participation and reduced wages in U.S. local labor markets that “house[d] import-competing manufacturing
industries” (Autor, Dorn, and Hanson, 2013). Similar research on local Mexican labor markets in currently underway at the Central Bank of Mexico, led by Daniel Chiquiar, with qualitatively similar results as those reported by Autor, Dorn and Hanson for the United States.\textsuperscript{5}

The rest of this paper is organized as follows. Section 2 describes the role of China as a competitor and source of demand in global markets. Section 3 explains the methodology, while section 4 contains the description of the data. The results are presented in section 5 and section 6 concludes.

\section{China as a Competitor and Source of Demand in Global Markets}

Since the early 2000s China has experienced an astonishing increase in its exports. Between 2001 and 2011 China’s exports increased 400\%, with manufacturing exports increasing 410\%.\textsuperscript{6} Moreover, Figure 1 shows that China increased its share in world exports from 7\% to 12\% in the same period, with manufacturing increasing from 7.6\% to 14\%. This large increase in exports suggests that China probably put downward pressure on world prices. For example, Amiti and Freund (2010) construct a price index for manufactured goods export from China to the US, finding a 12\% decrease in the price (unit values) between 1997 and 2005. This change in prices and global shares probably affected other countries’ exports, mainly those competing in the same markets. For instances Mexico share in global manufacturing exports decreased from 2.6\% to 2.1\% between 2001 and 2011. Similarly, if we choose those products in which China’s share in world exports increase by 50\% or more, and LAC represented at least 5\% in world exports, we find that LAC’s share in global export of these products decreased by 16\%, while the rest of the world (i.e excluding China) decreased its share by 14\%.

Although China’s exports can be seen as an increase in competition for some countries, its

\textsuperscript{5}See Handley and Limao (2013) for the effect of China’s growth on US consumers through uncertainty channels.

\textsuperscript{6}In current USD.
increasing imports offered export opportunities. China’s imports increased by 574% between 2001 and 2011. As Figure 1 shows, China increased its world import share from a 4% to 9% in the same period. This increase was especially important in the mining and agricultural sectors\textsuperscript{7}. China’s share in world imports of agricultural goods increased from 4.6% to 13.2%. China’s share in the world mining imports increased by 12 percentage points from 3% to 15%. Particularly, China’s imports from Brazil of mining goods in 2011 were 38 times its imports in 2001. At the same time, its imports of agricultural goods from Brazil in 2011 were 17 times its imports in 2001. Another example in Latin America is Argentina. China’s agricultural imports from Argentina in 2011 were 4 times its imports in 2001.

In sum, China has been playing two main roles in global trade: one as a large exporter of manufactured goods, probably pushing international prices downwards, and another as an important importer of mining and agricultural goods. These two roles impact Latin America exports and labor markets in opposite directions. The main aim of this paper is to analyze the net effect of these opposite forces on Argentina, Brazil and Mexico. Mexico is a good example of a country competing with China in the global manufacturing market, while Brazil and Argentina are good examples of countries that have increased they exports of mining and agricultural products.

\section*{2.1 China as a Competitor in Manufacturing}

The increase in China’s manufacturing exports probably had a greater impact on economies whose exports were more similar to China’s. To measure the degree of similarity between the exports of manufacturing goods between China and our three Latin-American countries we calculated the index proposed in Finger and Kreinin (1979). This index measures the proportion of exports from a pair of countries that are similar. More formally, the index is defined as:

\[ \text{Similarity}_{i,j} = \sum_{p \in P} \min(x_{p,i}, x_{p,j}) \]

\textsuperscript{7}Mining refers to mining plus utilities.
where \(i\) and \(j\) are countries, \(P\) is a group of products (for example manufacturing goods) and \(x_{p,i}\) is the share of product \(p\) in total exports of goods \(P\). Figure 2 shows the similarity index for manufacturing goods between our three Latin-American countries (Argentina, Brazil and Mexico) and three major exporters: China, the United States (US) and the European Union (EU).

It is clear that Mexico is the country whose manufacturing exports are more similar to those of China. In fact, the bundle of manufacturing exports of Mexico is more similar to China’s than to the US, which it is not the case for Brazil and Argentina. The manufacturing export bundles of Brazil and Argentina are more similar to US and EU’s. Thus, it is expected that China’s increased in manufacturing exports will have a greater effect on Mexico’s exports than Argentina or Brazil.

In order to show that the similarity is driven by products in which China increased its exports, we now present a dynamic revealed comparative advantage index. This index gauges the change in the share one country’s exports represents in a trading partner’s total imports of a product. More precisely the index is defined as:

\[
DRCA_{c,p,t_2,t_1} = \frac{M_{c,p,t_2}}{M_{world,p,t_2}} - \frac{M_{c,p,t_1}}{M_{world,p,t_1}}
\]

where \(M_{c,p,t}\) refers to imports of market \(M\) from country \(c\), of product \(p\), in period \(t\). This index tells us if exports from a country are gaining global market share in a particular product. If the DRCA is greater than zero, then country \(c\) is increasing its importance in country \(M\)’s imports of \(p\). Using this index we pay attention to two types of products: those under direct threat and those under strong-partial threat. We say that there is a direct threat if the DRCA of China is greater than zero and the DRCA of country \(c\) is less than zero, i.e if China is gaining share in a particular market while country \(c\) is losing participation in the same market. There is a partial threat if the DRCA is positive for both (China and country \(c\)). This partial threat is strong if the DRCA of China is greater than the DRCA of country \(c\), this is, although country \(c\) is gaining participation in a particular market, China is gaining even more participation in
the same market.

Figure 3 shows the number of products under direct and strong-partial threat for Argentina, Brazil and Mexico in three different markets: US, EU and the world. Figure 3 shows the percentage of manufacturing exports under the same types of threat in the same markets. In both graphs, the DRCA was calculated for every year with respect to 2001.

From Figure 3 it is clear that the number of products in which China has been gaining import market share respect to LAC is increasing, particularly in the EU market. Moreover, in the world market more than 80% of Mexico’s manufacturing exports seem to be losing importance vis-à-vis China. At the beginning of the 2000s about 80% of manufacturing exports from Mexico to US and the EU were also losing importance against China. Thus, it seems that China’s manufacturing exports are not only similar to Mexico’s exports but also; they are similar in products in which China has been gaining market share.

For Mexico, Figure 3 shows a decreasing trend in the fraction of exports that are under threat, particularly in the US market. This trend can be due to a crowding out of Mexican products by Chinese products. For example, let us say that 100% of Mexico’s manufacturing products were crowded out by China’s exports, then the percentage of Mexico’s exports under threat is zero, but only because it is exporting zero goods. Thus, the decreasing fraction of Mexico’s exports under threat in the US market can be due to a reallocation of products, and China’s exports might be part of the explanation of this reallocation.

In sum, if China is behind the change in manufacturing exports of these three countries, it is expected to have a greater effect on Mexico due to their similarity in their manufacturing export basket.

2.2 China as a Source of Demand

As noted above, China increased its share in world imports, particularly in agricultural and mining goods. Thus, China increased its importance as a trading partner for several countries, some of them in Latin America.
Figure 4 shows that in 2001 Brazil’s exports to China were about 4% of Brazil’s total exports, while in 2011 China represented around 20% in Brazil’s exports. In other words, China increased its importance as trading partner of Brazil by 16 percentage points in 10 years. This increase is mainly explained by the increase in mining exports. Exports of mining account for 11 percentage points of the 16 percentage points, while agriculture explains about 4 percentage points.

China also increased its importance as a trading partner of Argentina and Mexico. As Figure 4 shows, from 2001 to 2011, China increased its importance in Argentina’s exports by about 3 percentage points. An increase in agricultural exports explains 2 out of 3 percentage points. The increase of Mexico’s exports to China, in the same period, is about 1.6 percentage points, half of them explained by an increased in mining exports.

On one hand, China increased its exports of manufacturing goods, which increased the global supply these products, affecting Latin American exports. On the other hand, China has increased its imports of mining and agricultural goods, also affecting Latin American exports, but in the opposite direction. Which opposing force dominates the other: The increase in the global demand for Latin American agriculture and mining exports or the decrease in residual demand for manufacturing exports? The rest of the paper tackles this question.

3 Methodology

3.1 “China Effect” on Net Exports

Our goal is to develop an index that can capture the changes in net demand, faced by exporters, that are uncorrelated with local market conditions in Latin America. Unfortunately, it is quite difficult to identify the changes in net exports caused directly by China empirically, since there are many other relevant shocks that can shift import demand and export supply curves; domestic shocks can easily dominate the shocks caused by China. Therefore we deliberately abstain from using bilateral trade data between Latin American and other countries,
which are subject to shocks unrelated to China. However, we can conveniently assume that
differences in China’s export market share in manufacturing and import market share in mining
and agriculture (relative to the rest of the world) were exogenous to local conditions in Latin
America.

Moreover, the competition faced by manufacturing exporters can be quite different based
on the products they export. Some countries’ exports overlap with China’s export composition
more than others. For example, Mexico’s manufacturing exports are similar to China’s exports
while Brazil’s manufacturing exports are quite different. The same logic applies to imports.
Therefore, export and import composition of a country can affect its exposure to the potential
threats and opportunities brought by the rise of China in global markets.

Appendix I presents a detailed derivation of the vulnerability index. In short, to calculate
the export vulnerability of a sector, for each four-digit industry subcategory we calculate the net
increase in China’s share of world trade adjusted by the size of the ROW in world’s exports.
Then, we calculated a weighted average of these increases, where the weights are the initial
share of each product in country $i$’s total manufacturing exports. The following equation gives
us the export vulnerability index, which is expressed as a percent change in country $i$’s total
sectoral exports:

\[
\tilde{X}^i = \sum_{g \in G} \left[ \left( \frac{X^c_{g,t_2}}{X^W_{g,t_2}} - \frac{X^c_{g,t_1}}{X^W_{g,t_1}} \right) \frac{X^W_{g,t_1}}{X^W_{g,t_1}} \sum_{g' \in G} \frac{X^i_{g',t_1}}{X^W_{g',t_1}} \right],
\]

where $X^C_{g,t}$ is China’s exports of product $g$ at time $t$, $X^W_{g,t}$ is the total exports in the world, $X^i_{g,t}$
is country $i$’s exports, and $G$ is the set of all products in a particular sector, according to the
ISIC classification. The minus sign at the beginning of (1) tells us that exports in the ROW
decrease if China’s share in world’s exports increases.

As mentioned, the index is a function of the export composition of the origin country. For
example, if Mexico’s exports and China’s exports are unrelated, then the index will be zero. It
is important to note that we assume perfect substitutability of Chinese exports and country $i$’s exports at the 4 digit level of aggregation.

We develop a similar index to calculate the increase in the import demand faced by Latin American economies due to China’s growth. This opportunity index is equal to

$$
\hat{X}^i = \sum_{g \in G} \left[ \left( \frac{M_{g,t_2}^C}{M_{g,t_1}^W} - \frac{M_{g,t_1}^C}{M_{g,t_2}^W} \right) \frac{X_{g,t_1}^W}{X_{g,t_1}^{ROW}} \sum_{g' \in G} \frac{X_{g',t_1}^i}{X_{g',t_1}^{ROW}} \right],
$$

where $M_{g,t}^C$ is the product $g$ imports of China at time $t$ and $M_{g,t}^W$ is total imports in the world. This is the same index as (1) assuming that China’s exports are equal to the -additive- inverse of imports and that world’s imports equal world’s exports.

Note that we use the increase in China’s share in world imports instead of using the increase in country $i$’s exports to China. We avoid using bilateral data because they are affected by both import demand and export supply shocks. The objective is to isolate the exogenous import demand shock from export supply shocks.

In order to have an estimate of the increase or decrease in net exports of a sector in country $i$, we calculate the difference between the opportunity and vulnerability indices. In reality, the actual change in country $i$’s net exports can be quite different from the amount implied by the indices. Because the indices only capture the shocks caused by the growth of China, assuming there are no other exogenous changes, particularly in local market conditions. Note that we are not interested in calculating the observed change in exports per se, but the change in exports that can be attributed to China, net of all other exogenous shocks.

It is useful to discuss the underlying assumptions under which the indices can capture changes in country $i$’s net exports:

1. All products from all origins within category $g$ are perfect substitutes produced in perfectly competitive markets, and they are unrelated to products in other categories. The level of aggregation of the trade data might affect the validity of this assumption. For example,
if the level of disaggregation is high, then different categories of products can become closely related to each other. In order to avoid this problem, we do not go beyond the 4 digit level of the ISIC classification\(^8\).

(2) The exogenous product \( g \) shocks originating from China are approximately equal for the Latin American producers and for the rest of the world. This assumption may be violated if competition is localized due to high transportation costs. For example, the increase in Chinese exports might affect Vietnamese exporters more severely than Mexican exporters as a result of Vietnam’s proximity to China.

This said, we calculated the vulnerability and opportunity indexes for manufacturing, mining and agricultural products in Argentina, Brazil and Mexico. The difference between these indices tell us how much net exports were expected to increase (or decrease) because of China’s rapid growth for a typical country with given initial export structure, assuming everything else stays the same. Then we use the model presented in the next section to calculate corresponding price changes in each economy. This is the required price change to match the change in net exports within our neo-classical model calibrated with Latin American data. For example, we calculate how much the manufacturing prices should decline to account for the change implied by the net export index (i.e the difference between the opportunity and vulnerability indices in manufacturing).

### 3.2 A Model of Labor Adjustment in a Small Open Economy

We use the informal and formal labor mobility framework introduced by Arias et al (2013). Consider an economy with perfectly competitive \( N + 1 \) sectors and \( N \) products. The last sector is the residual (or non-market) sector, which is not related to any product. Each sector, apart from the non-market sector, has an informal and a formal sub-sector. For example, manufacturing goods can be produced either in the formal manufacturing sector or in the informal manufacturing sector. In addition to perfectly competitive producers, there is a fixed

\(^8\)We have experimented with different aggregation levels, such as ISIC 6, and found that the proposed index is robust.
number of risk-neutral workers whose decisions constitute the labor supply equations.

3.2.1 Labor Supply

Workers are distributed across $2N + 1$ sub-sectors: A worker in sector $i$ receives wage $w^i_t$ at time $t$. In addition to the wage, workers receive a sector specific common utility $\eta^i$ while working in sector $i$. The fixed utility $\eta^i$ accounts for compensating differentials, such as working conditions, hours, benefits, on-the-job hazards, etc. Therefore, the sector with the highest wage is not necessarily the most attractive one. We assume that both the wage $w^i_t$ and the fixed utility $\eta^i$ are common for all workers in sector $i$, hence workers are ex-ante identical (within sectors).

Workers have an option to change their industry of employment in every time period. However, workers face moving cost frictions, and have to pay a utility cost if they decide to move. The moving cost has two components: a fixed moving cost common to all workers, and a random idiosyncratic component that is worker-specific in every time period. When a worker moves from sector $i$ to $j$, she pays the fixed moving cost $C^{ij}$ and a random idiosyncratic worker-specific cost $\epsilon^i_t - \epsilon^j_t$, where the random variable $\epsilon^i_t$ follows an “extreme value” distribution with scale parameter $\nu$, which is proportional to the standard error. The moving cost captures all labor market frictions that restrict worker mobility across sectors, and it should not be interpreted (only) as the literal cost of moving. Stayers do not pay the moving cost, i.e. $C^{ij} = 0$ if $i = j$. Due to the idiosyncratic component of the moving cost, workers are ex-post different from each other.

In the dynamic equilibrium, workers choose the optimal sector after taking wages, fixed utility, fixed moving costs, random moving costs into account by calculating their expected future values. Workers are rational, risk neutral, live infinitely and discount the future with parameter $\beta$. The optimal sector for a worker may not be the one with the highest wage and fixed utility because of the moving costs and workers’ expectations about the future. Under the rational expectations assumption, workers have an expectation about future wages but their
expected wages do not necessarily equal the revealed wage in the data. That is, workers can make errors in their guesses about the future, but the errors cannot be systematic, i.e. workers cannot persistently underestimate or overestimate future wages. Our econometric strategy does not require parameterization of workers’ expectations, however.

The optimization problem is expressed by the following equation

\[
V_i^t = w^t + \eta_i + \beta E_t \max_j \{ V_j^{t+1} - C^{ij} - \epsilon_i^{t+1} \},
\]

where \( V_i^t \) is the present discounted value of the workers’ utility in sector \( i \). The choice-specific Bellman equation is

\[
V_i^t = w^t + \eta_i + \beta E_t V_i^{t+1} + \beta \Omega_i^{t+1},
\]

where \( \Omega_i^{t+1} \) is the “option value of moving”, which is equal to the expected benefit of moving conditional on the net benefit of moving being positive. The “option value of moving” can be solved analytically when \( \epsilon^t_i \) is an i.i.d random variable that follows a “extreme value” distribution.

The labor flows can be expressed as

\[
y_{ij}^t = \frac{\exp \left( \left( EV_j^{t+1} - EV_i^{t+1} - C^{ij} \right) \frac{1}{\nu} \right) \nu \left( \sum_{k=1}^{2N+1} \exp \left( \left( EV_k^{t+1} - EV_i^{t+1} - C^{ik} \right) \frac{1}{\nu} \right) \right)}{\sum_{k=1}^{2N+1} \exp \left( \left( EV_k^{t+1} - EV_i^{t+1} - C^{ik} \right) \frac{1}{\nu} \right) \nu},
\]

where \( y_{ij}^t \) is the number of workers moving to sector \( j \) from sector \( i \) and \( L_i^t \) is the total number of workers in sector \( i \).
3.2.2 Production, Consumption and Net Exports

We assume that formal and informal sub-sector products are perfect substitutes. However, consistent with existing literature, workers are less productive when they are employed in the informal sector as opposed to formal sectors. This assumption is also consistent with the lower informal wages observed in the data. The effective total human capital in an industry $i$ can be expressed as

\[ L_i^t = a_j^j L_j^t + a_k^k L_k^t, \]  

where $j$ and $k$ are the formal and informal sub-sectors of industry $i$. $a_j^j$ is the productivity parameter in the formal sector $j$, and $a_k^k$ is the productivity of the workers in the informal sector $k$. Assuming Cobb-Douglas production, output $q_i^t$ in main-industry $i$ at time $t$ is equal to

\[ q_i^t = A^i(K^i)^{1-\gamma_i}(L_i^t)^{\gamma_i}, \]

where the labor share is $\gamma_i$ and the stock of capital is $K^i$.

From the production function (7) and equation (6), we can derive the marginal product of labor for a worker of type $k$ in sector $i$. Equating the wage to the value of the marginal product of labor, we obtain the wage equation:

\[ w_s^t = \frac{p_i^s}{P_t} a_s^s \gamma_i A^i(K^i)^{1-\gamma_i}(L_i^t)^{\gamma_i-1}, \]

where $s$ is the formal or informal sub-sector of sector $i$, $P_t$ is the aggregate price index, $p_i^s$ is the unit price of sector $i$ output and $w_t$ is the real wage in terms of $P_t$.

We close the model with the following consumer price index equation
(9) \[ P_t = \prod_{i} (p_i^t)^{\theta_i}. \]

with consumption shares \( \theta_i \).

Given the Cobb-Douglas preferences, the domestic consumption of sector \( i \) product, \( c_i^t \), can be expressed as

(10) \[ c_i^t = \theta_i \frac{M_t}{p_i^t}, \]

where the income \( M_t \) equals \( M_t = \sum_i p_i^t q_i^t \).

We pin down prices by setting \( q_i^t = c_i^t \) in the non-tradable sectors \(^9\). In the traded sectors, the net exports are equal to

(11) \[ X_i^t = q_i^t - c_i^t, \]

It is useful to write the net exports relative to time \( t_0 \) variables for calibration purposes:

(12) \[ X_i^t = \frac{q_i^t}{q_{i_0}^t} - \frac{c_i^t}{\bar{c}_{i_0}}, \]

where \( \tilde{q}_{i_0}^t \) and \( \bar{c}_{i_0}^t \) are production and consumption of product \( i \), and they can be directly plugged in from the data \(^{10}\).

\(^9\)In this paper, the non-tradable sectors are: construction, retail and other services.

\(^{10}\)Particularly from Input-Output tables.
3.3 Estimation, Parameterization and Calibration

Our econometric strategy relies on estimating expected values from the data. Previously in the literature, Hotz and Miller (1993) showed how expected values can be imputed from conditional choice probabilities. They introduce an inversion equation that maps probabilities to values and estimate conditional choice probabilities with a non-parametric method. In a departure from the literature, we use a Poisson Pseudo Maximum Likelihood (PPML) regression to estimate expected values instead of the Hotz and Miller (1993) inversion equation. PPML is used in the international trade literature to estimate the gravity model as in Santos Silva and Tenreyro (2006) and Anderson (2011). The use of PPML is intuitive and simplifies the estimation procedure significantly. With an infinitely large sample, Hotz-Miller inversion equation and PPML give identical results. However, PPML performs better if the sample has many zeros due to small sample (as it is usually the case with developing country data).

The following variables are taken directly from the data: Wages, \( w_{it} \), the distribution of workers, \( L_i \), and labor flows, \( y_{ij} \). The discount factor \( \beta \) is fixed at 0.95 and the variance parameter \( \nu \) is set to 0.6 following the literature.\(^{11}\) The moving cost parameter, \( C_{ij} \), the values \( EV_{it} \) and the option values \( \Omega_{it} \) are estimated. The remaining fixed utility parameters, \( \eta_i \), and production function parameters are calibrated from the data.

**Stage 1: The Flow Equation**

The labor flow equation (5) can be estimated with a PPML regression similar to the gravity equation, where the entry costs create a bilateral resistance term similar to distance. The labor flow equation can be expressed as a PPML regression such that

\[
(13) \quad y_{ij} = \exp \left( \Gamma_{it} + \Lambda_{jt} + 1_{i \neq j} \delta_{ij} \right) + e_{ij}.
\]

\(^{11}\)It is possible to estimate \( \nu \) with longer time series. For example, Artuğ et al (2010) use a time series of 26 years. Although, our estimator is more efficient, we do not have sufficiently long time series to pin down \( \nu \). See the technical note by Artuğ (2013) for details.
$\Gamma_i^t$ is the coefficient of the origin-industry fixed effect; $\Lambda_j^t$ is the coefficient of destination-industry fixed effect$^{12}$; and $\delta^{ij}$ is the normalized fixed entry cost to sector $j$ from sector $i$. $\mathbf{1}_{i \neq j}$ is the indicator function that equals one if $i$ is different from $j$ and zero otherwise (i.e. when $y_{it}^{ij}$ corresponds to movers rather than stayers). $e_{ij}^t$ is the regression residual.

The structure of the moving cost matrix $\delta^{ij}$ is flexible. Workers pay an entry cost that is a function of the destination sector and workers’ original formality status. Thus, we assume the following moving cost structure:

\[
\delta^{ij} = \begin{cases} 
\Delta_1^i, & \text{from an informal sector to formal } j \text{ without changing the main industry}, \\
\Delta_2^i, & \text{from a formal sector to informal } j \text{ without changing the main industry}, \\
\Delta_3^i, & \text{from any informal sector to formal } j \text{ while changing the main industry}, \\
\Delta_4^i, & \text{from any formal sector to formal } j \text{ while changing the main industry}, \\
\Delta_5^i, & \text{to informal } j \text{ while changing the main industry (from any sector),}
\end{cases}
\]

where $i$ is the origin sector and $j$ is a formal or informal destination sector, such as informal manufacturing or formal services. The main industries are: 1. Agriculture, 2. Mining and Utilities 3. Manufacturing, 4. Construction, 5. Trade, 6. Hotels and Restaurants and, 7. Other Services. Each main industry consists of an informal and a formal sector. Therefore there are $2 \times 7 + 1 = 15$ sectors including the “residual” sector. For example, if a worker moves from informal manufacturing to formal manufacturing (that is, without changing the main industry), she faces the moving cost $\Delta_1^i$. If a worker moves into informal manufacturing from formal services, she faces the moving cost $\Delta_5^i$. If a worker moves from formal manufacturing to formal service she faces the moving cost $\Delta_4^i$.

The $j$-specific term or the destination fixed effect, $\Lambda_j^t$, is equal to

$^{12}$Note that, we need to drop either destination or fixed effect for one choice (i.e. normalize the choice specific values). Otherwise, the regression matrix becomes singular because only the value differences between choices are identifiable from the choice data.
(15) \[ \Lambda^i_t = \frac{\beta}{\nu} E_t V^i_{t+1} - \frac{\beta}{\nu} E_t V^1_{t+1} , \]

the \( i \)-specific term or the origin fixed effect, \( \Gamma^i_t \), is equal to

\[
(16) \quad \Gamma^i_t = -\frac{\beta}{\nu} E_t V^i_{t+1} - \frac{1}{\nu} \Omega^i_t + \log(L^i_t) + \frac{\beta}{\nu} E_t V^1_{t+1},
\]

and the moving cost term, \( \delta^{ij} \), is equal to

\[
(17) \quad \delta^{ij} = -\frac{1}{\nu} C^{ij}.
\]

Finally, using destination and origin fixed effects, we construct the option value term, \( \Omega^i_t \), as

\[
(18) \quad \frac{1}{\nu} \Omega^i_t = -\Lambda^i_t - \Gamma^i_t + \log(L^i_t).
\]

See Appendix II for the details of the estimation strategy. The remaining parameters \( \eta^i \) and \( \nu \) are calibrated in the second stage. After calibrating, \( \eta^i \), and the production functions, the model can be fully parameterized.

**Stage 2: Parameterization and Calibration**

The estimation procedure gives us the dynamic labor supply equations. In order to derive the labor demand and net export equations, we need to parameterize the production and consumption functions. Without loss of generality, we normalize the productivity parameter to unity for formal workers, i.e \( \alpha^j = 1 \) for formal sector \( j \). Also, by assumption, the informal productive multiplier is equal to \( \alpha^k = w^k_t/w^1_t \) where \( k \) and \( j \) are, respectively, the informal and formal sub-sectors of the same sector. The \( \alpha^k \)'s are easily pinned down from observed average
wages.

We pin down the Cobb-Douglas labor shares from the ratio of an industry’s wage bill over the industry’s value added (which comes from national input-output tables\textsuperscript{13}). The wage equation multiplier $A_i$ is calibrated such that the aggregate labor allocation reflects the observed average wage in the data from each country. Finally, the fixed utility parameters, $\eta^i$, are calibrated by matching the simulated labor allocations with the labor allocations observed in the data.

### 3.4 Simulations

We simulate the effect of China on each country with a one-time change in the world prices of manufacturing, mining and agriculture at the same time. We assume that China’s growth in exports and imports causes the price faced by Latin American exporters to change, since producers face perfectly elastic demand in a perfect competition setting. Consistent with this, we assume that Argentina, Brazil and Mexico are small open economies, i.e. they take prices as given. However, the difference between the vulnerability and opportunity indices gives us the change in net exports but not in prices. Therefore, we need to map the change in net exports (which is endogenous in our model) to a exogenous price change.

The price effect of China is endogenous estimated with the calibration of the model. The calibration is performed with the estimated moving-costs parameters and the other parameters computed from the observed data as discussed above. In the first iteration, we shock the model with a guess of the price effect of (only) one sector and we use it to calculate the reduction in net exports over time (see equation 12). Then we compare the change in net exports with the difference between the opportunity and vulnerability indices we described previously (see equations 1 and 2). If the change in net exports equals the difference between the indices we stop. If the change in exports is not equal to the difference between indices we apply another price reduction. The algorithm tries different price shocks until it finds an equilibrium where

\textsuperscript{13}We used the IO table of 2003 for Mexico, 2005 for Brazil and 1997 for Argentina. The sources are the INEGI, IBGE and INDEC respectively.
the long run reduction in simulated net exports is equal to the reduction implied by the indices, for each sector separately.

Then we simulate the model applying the change in prices of all the three sectors at once. The simulations are conducted by calculating the equilibrium values of $V_i^t$, $L_i^t$, $p_i^t$ for every $i$ and $t$, using the equations described in the previous subsection. The simulation method is based on a shooting method similar to Lipton et al (1982).

When we shock the system by changing the price of one product (i.e through a demand shock), labor supply and wage differentials change for all sectors in the general equilibrium setting. Therefore, a demand shock for one sector creates supply shocks in other sectors. Our goal is to calibrate the price change in a particular sector to match a specific demand shock implied by the index, *ceterus paribus*. Therefore, we have to calibrate price changes separately for each demand shock (as opposed to calibrating them together at once), without contaminating the system with shocks originating from other sectors 14.

We compute the perfect-foresight path of the adjustment following the one-time price shock. The simulated adjustment process continues until the economy effectively reaches the new steady state. This requires that each worker –taking the time path of wages in all sectors as given– optimally decides at each date whether or not to switch sectors, while taking into account workers’ own idiosyncratic or personal shocks. This computation yields a time path for the allocation of workers, as well as the time path of wages, since the wage in each sector at each date is determined by market clearing conditions from equation (8)15.

14. To check robustness of the results, we calibrated price changes simultaneously for all demand shocks and found that the general equilibrium effects are not large enough to affect the results significantly.

15. The simulations were also run using the opportunity indexes of agriculture and mining as well as the vulnerability index of manufacturing instead of the net effect. Moreover, we also simulate each price change separately. The main results are qualitatively similar to those of the net effects. Results are available upon request.
4 Data

The estimation of the labor mobility costs is conducted using Labor Force Surveys (LFS) from Brazil, Mexico, and Argentina. A common feature of these surveys is their rotative panel structure that permits the construction of employment transition matrices. We restrict the sample to individuals between 15 and 65 years of age. The industries are aggregated into seven sectors: i) Agriculture, ii) Mining and Utilities, iii) Manufacturing, iv) Construction, v) Commerce, vi) Hotels and Restaurants, and vii) Other Services. Each sector is further divided into formal and informal. A worker is considered informal if she is not registered in the social security system. Additionally, there is a residual sector that captures individuals who are either unemployed or out of the labor force.

The “Encuesta Nacional de Ocupacion y Empleo” (ENOE) is used to compute the transition matrices for Mexico. The ENOE is a household survey that collects detailed information on labor force status, wages, occupational and demographic characteristics. It is collected quarterly since 2005, and it is representative at both the national and state levels. The sample size is around 120,260 households in each quarter. Each household is interviewed in five consecutive quarters. In each quarter, one fifth of the sample (e.g., households in their fifth interview) is replaced. We construct the transition matrix by looking at the first and fifth interview. We derive six year-on-year transition matrices, the first matrix reflecting transitions between 2005 and 2006 and the most recent between 2010 and 2011.

The “Pesquisa Mensal de Emprego” is the Brazilian LFS. The survey collects detailed information of Brazil’s labor market and it is representative of only six metropolitan (urban) regions. Each wave of the survey has approximately 120,000 individuals. The panel structure consists on each household being interviewed 12 times over an 18-month period. In each wave of the survey, we identify individuals in their first interview and we follow them a year later at the time of their fifth interview. We computed four year-on-year transitions matrices that cover the period between 2007 and 2011.

The “Encuesta Permante de Hogares” (EPH) is used to compute the transition matrices
for Argentina. It is collected quarterly since 2003, and it is representative of the urban areas. The sample size is around 17,000 households in each quarter. Each household is interviewed in two consecutive quarters and then again in the same two quarters of the following year. We construct the transition matrices by comparing the sector of employment of the individual in the first and third interviews. We derive seven year-on-year transition matrices, the first matrix reflecting transitions between 2004 and 2005 and the most recent between 2010 and 2011.

The simulation exercises require information on key parameters, including labor shares and consumption shares by sector for each country. Complementary data sources were required to compute these parameters. The labor shares were defined as the ratio of the wage bill over total value added for each sector. These parameters were calculated from input-output (IO) tables from Mexico, Brazil and Argentina. We used the IO table of 2003 for Mexico, 2005 for Brazil and 1997 for Argentina. Average formal and informal wages were calculated with data from the Labor Force Surveys (LFS). We use CPI hasket shares along with input-output tables on consumption expenditures to calibrate the utility function parameters. The parameters for the simulations are shown in Table 1.

5 Results

This section presents three sets of results. The first set of results is related to the direct effect of China’s trade on LAC’s exports. This direct effect of China is calculated for three sectors (manufacturing, agriculture and mining) and 29 Latin American countries, using our vulnerability and opportunity indexes. The second set of results are the PPML estimation of the workers’ perceived entry costs. These costs are associated with movements across industries as well as with movements in and out of formality. Finally, the estimated entry costs and the net-exports effects are utilized to simulate the total effect of China’s trade on Argentina, Brazil and Mexico’s labor markets.
5.1 The China Effect on Exports

As explained in the methodology, the vulnerability index before China’s change in manufacturing, agricultural and mining exports, was calculated as a weighted average of the change in China’s share in global exports of the each sector (adjusted by the size of the rest of the world (ROW), i.e the world excluding China). Similarly, the opportunity index of China’s increase in imports -of manufacturing, mining and agriculture- was calculated as a weighted average of the change in China’s share in world’s imports (adjusted by the size of the ROW). The net index is defined as the difference between the opportunity and vulnerability indices. The net index shows that Brazil, Argentina and Mexico are between the countries with the largest effect in mining, agriculture and manufacturing, respectively; making them suitable to analyze shocks in these sectors.

Figure 5 shows the opportunity and net China effect on LAC’s mining exports. Brazil appears with the highest net effect among all the countries in the sample, mainly due to the increase of iron ore exports. According to our index, China’s increase in mining imports -from 2001 to 2011- would increase Brazil’s exports of mining by 33%. Following Brazil, the second country with the highest effect is Chile, one of the most important exporters of copper. The net effect on Chile’s exports of mining is about 26%. At the bottom are countries like Costa Rica and El Salvador, which do not have an important extractive industry.

Figure 6 shows the opportunity and net effect of China on LAC’s agricultural exports. At the top are countries like Paraguay, Argentina, Guyana, Brazil and Uruguay. The largest effect is found for Paraguay, with a (positive) effect of about 16%. The second largest effect is found for Argentina, with 13%, followed by Guyana and Brazil, both with an effect close to 11%.

Figure 7 shows the vulnerability and net effect on LAC’s manufacturing exports. The most affected countries were Haiti and Honduras. For these countries, textiles where among the most important manufacturing exports in 2001. The calculated effect was 19% and 16% for Haiti and Honduras respectively. Mexico was hit by 11%. Different from Haiti and Honduras, the effect on Mexico was not concentrated in textile exports; it was distributed across more products,
including office and accounting machinery as well as television and radio transmitters. With a positive effect are countries like Bolivia, Paraguay, Suriname and Cuba, which exported few manufactured products that overlapped with China.

Table 2 shows the implied change in prices for Argentina, Brazil and Mexico, which were estimated with the iterative simulation procedure. The decrease of 11% in Mexico’s manufacturing exports is associated with a price shock of 12%. Similarly, the implied change in mining price for Brazil is about 27%, while Argentina’s agricultural price change is about 10%.

### 5.2 Labor Mobility Costs

Table 3 shows the estimates of (normalized) labor mobility costs. Assuming \( \nu = 0.6 \), these costs should be interpreted as entry costs in terms of multiples of annual average real wages times 0.6 in each country. As in Arias et al (2013), there are three common results. First, it is less costly to become formal if the worker stays in the same industry. Second, the highest entry costs involve moving from informal to formal and changing the sector of employment. Third, the lowest entry costs are associated with movements from formal to informal within the same sector.

In Argentina and Mexico the lowest entry costs are found in movements from formal to informal employment within the restaurant-and-hotels sector. In Brazil the lowest entry cost is associated with movements from formal to informal within agriculture. Moreover, in the three countries the highest cost is found in movements from informal to formal employment while changing sector into agriculture or mining. This limits the movement of workers into these sectors, which are precisely the ones that were positively shocked by China.

As argued above, the sector most directly affected by China within Brazil is the mining sector, while the agricultural and manufacturing sectors are the main affected sectors in Argentina and Mexico, respectively. Given the estimated entry costs, what are the main movements expected to/from other sectors? An increase in labor demand in the Brazilian mining sector is expected to increase people moving to mining. A higher labor demand in the agricultural
sector in Argentina is expected to increase informal employment rather than formal; while an increase of mining labor demand in Mexico is expected to provoke a movement of labor from other formal sectors to formal employment in mining. Moreover, a decrease in labor demand in the manufacturing sector, in general, is expected to provoke a movement of labor to commerce or to the residual sector.

5.3 Simulations

As in Arias et al (2013), the analysis assumes that: 1) the domestic price of each good at date $t = -1$ is unity, 2) at $t = 0$ the domestic prices change according to Table 2, and, 3) the changes in prices are assumed to be permanent. We computed the perfect-foresight path of the adjustment, following the shock in prices. The simulated adjustment process continues until the economy effectively reaches the new steady state. This computation yields a time path for the allocation of workers and wages in each sector.

Figures 8 to 10 show the simulations for Argentina. As expected for Argentina, the employment in the agricultural sector increases in both the formal and informal sector. The agricultural formal sector increases by 14% and the informal agricultural sector increases by around 6%. The labor in the mining sector also increases, but less than in agriculture. The formal employment in mining increases by 4%, while the informal by 1%. Moreover, the shocks provoke a decrease in the manufacturing sector. Formal manufacturing decreases by 1%, while informal manufacturing decreases by 0.5%.

The percentage effects are greater for agriculture and mining than manufacturing but manufacturing is a larger sector. Formal manufacturing employs about 9 times the number of workers that formal mining employs and about 45 times the number of workers in formal manufacturing. Informal manufacturing employs about 41 times more workers than informal mining and 8 times more than informal agriculture. Since manufacturing employs more workers than the other two sectors, its negative effect on employment offset the positive effect of agriculture and mining, at the aggregated level. Thus, the aggregate effect on employment is near zero,
as shown in Figure 9. The decrease in the residual sector is about 0.3%. Thus, in general, the negative shock in manufacturing is offset by the positive shock in agriculture and mining.

Figure 10 shows the adjustment path of real wages in Argentina. Right after the shock, wages increase in agriculture and mining and fall in manufacturing, as the demand for labor increases in the two first sectors and decreases in manufacturing. In the long run, as labor is reallocated between sectors, wages tend to move towards their initial level. In the new steady state there is an increase in agriculture real wage (of about 2.6%), while the real wages in the other sectors remain at the original level.

In sum, in Argentina, the positive shock on agriculture and mining is offset by the negative shock in manufacturing, keeping wages and the aggregate level of labor almost at the same original level before the shocks. Although the aggregate level of labor remains constant in the long run, we should notice that there is a reallocation of it from the manufacturing sector to the agriculture and mining sectors.

Similar results are found for Brazil. Figure 11 shows increases of about 35% in the employment level of the formal mining sector and 14% in informal mining. Moreover, there is an increase of about 2% in the number of workers in formal agriculture. In contraposition to these increases in the positively shocked sectors, there is a decrease in the number of workers in the negatively shocked sector, namely manufacturing. The number of workers in formal manufacturing decreases by about 3%, while they decrease by 2% in the informal manufacturing sector. As in Argentina, the manufacturing sector employs substantially more workers than mining and agriculture, which offset the positive effect in employment. As Figure 12 shows, the residual sector decreases by about 0.1%. Thus, as in Argentina, the negative shock on manufacturing is offset by the positive shock in mining and agriculture, leaving the aggregate level of employment similar to the level before the shock. Moreover, in $t = 0$, when the shocks hit the economy, there is an increase in mining real wages of about 28%, although, as people move out of manufacturing to this sector, increasing the labor supply, real wages start to drop increasing only 2.3% in the new steady state.
In short, there is a reallocation of labor from manufacturing to mining and agriculture, leaving real wages and the aggregate level of employment almost without change in the long run. In the short run there is an increase in real wages in the mining sector.

Figures 14 to 16 shows the simulations for Mexico. Similar to Brazil and Argentina, there is an increase in formal and informal employment in agriculture and mining, as well as a decrease in formal and informal manufacturing employment. In the informal sector, the employment in manufacturing decreases by 2.6%, while mining increase by 6% and agriculture by 3%. In the formal sector, manufacturing decrease its number of workers by about by 6.3%, while mining increase their number of workers by 15% and agriculture by 2.5%. At the aggregate level, total employment decreases. As Figure 15 shows, the residual sector increases by 2% in the long run. In the short run, there is an important increase in mining real wages (of 16.6%) and a substantially decrease in manufacturing real wages of about 5%. But in the long run, there is only a slightly decrease in manufacturing real wages and a slightly increase in mining real wages.

In sum, for Argentina and Brazil, the positive shocks in agriculture and mining offset the negative shock in manufacturing leaving the total level of employment and real wages almost at the same initial level. Note that, in these two countries, a larger positive shock in mining and agriculture is needed to offset a smaller shock in manufacturing, because this sector employs a larger proportion of workers. In Mexico, the larger shock in manufacturing provokes a reduction of employment in the long run. In Argentina and Brazil the re-allocation of labor goes from the manufacturing sector to the agricultural and mining sectors, while in Mexico the re-allocation of labor goes from the manufacturing sector to the agriculture and mining sectors.

6 Conclusions

This paper analyzed the effects of China on Latin America’s trade and labor markets. Regarding the change in exports, the opportunity and vulnerability indexes suggest sizable effects on Latin America. Specifically we found important negative effects on manufacturing
exports for countries such as Haiti, Honduras and Mexico. On the other hand, we found positive effects on agricultural exports for countries like Paraguay, Argentina, Guyana, Brazil and Uruguay and also positive effects on mining exports for Brazil, Chile, Honduras and Peru.

The China-related trade shocks affected LAC labor markets characterized by high labor mobility costs, which drive a notable wedge between the short- and long-run impacts on relative wages and employment in Argentina, Brazil and Mexico. The highest mobility costs were found for workers switching from informality into formal jobs in agriculture or mining. This high mobility cost limited both the number of workers absorbed by these sectors and the reduction in informality induced by the favorable China effect.

The results of the simulations indicate that for Argentina and Brazil the positive shocks on agriculture and mining offset the negative shock on manufacturing, thus leaving the total level of employment and real wages almost at the same initial level in the long run. In these countries, a larger positive shock in mining and agriculture was needed to offset a smaller shock in manufacturing because the latter employed a larger proportion of workers. In the short run there was an increase in real wages in the mining and agricultural sectors.

In Mexico, however, the shock to manufacturing provoked a reduction in employment in the long run. In the short run, there was an increase in mining real wages and a decrease in manufacturing real wages.
References


Appendix I: Derivation of the China Effect Index

For each good $g$ in group $G$, let us take China’s and World’s exports in $t_i$ as given. This implies that we take the rest of the world’s \(^{16}\) (ROW) share in world exports as given. Moreover, let a country $i$’s export growth rate of good $g$ between $t_1$ and $t_2$ be equal to $r^i_g$. Then,

\[(19) \quad X^i_{g,t_2} = (1 + r^i_g)X^i_{g,t_1}\]

Total exports of $G$ goods are obtained by summing over all products $g$,

\[X^i_{G,t_2} = \sum_{g \in G} X^i_{g,t_2} = \sum_{g \in G} (1 + r^i_g)X^i_{g,t_1}\]

The percent change in total exports of $G$ between $t_1$ and $t_2$ is calculated dividing the latter expression by the total exports of $G$ goods in $t_1$ (and subtracting 1)

\[(20) \quad \text{Index} = \sum_{g \in G} r^i_g \frac{X^i_{g,t_1}}{\sum_{g' \in G} X^{i'}_{g',t_1}}\]

As we want to distribute the growth of China between the economies of the ROW, excluding other sources of export growth, we assume that world exports do not change from $t_1$ to $t_2$, i.e we assume that China’s exports growth crowds out the ROW in the same amount. This assumption implies that $X^W_{g,t_2} = X^W_{g,t_1}$. Moreover, we assume that $r^i_g$ does not depend on $i$. Using these two assumptions we can rewrite (19) as

\[(21) \quad \frac{X^i_{g,t_2}}{X^W_{g,t_2}} = \frac{1 + r^i_g}{1 + r^W_g} \frac{X^i_{g,t_1}}{X^W_{g,t_1}}\]

\(^{16}\)The rest of the world is defined as the world excluding China.
From this relation ROW exports in $t_2$ can be calculated as

$$X_{g,t_2}^{ROW} = \sum_{i \in ROW} X_{g,t_2}^i = (1 + r_g) \frac{X_{g,t_2}^W}{X_{g,t_1}^W} \sum_{i \in ROW} X_{g,t_1}^i$$

$$\Rightarrow X_{g,t_2}^{ROW} = (1 + r_g) \frac{X_{g,t_2}^W}{X_{g,t_1}^W} X_{g,t_1}^{ROW}$$

Since we take ROW exports as given, from this expression we can define $r_g$ as

$$r_g = \left( \frac{X_{g,t_2}^{ROW}}{X_{g,t_2}^W} \right) \left( \frac{X_{g,t_1}^W}{X_{g,t_1}^{ROW}} \right) - 1$$

$$= \left( 1 - \frac{X_{g,t_2}^c}{X_{g,t_2}^W} \right) \left( \frac{X_{g,t_1}^W}{X_{g,t_1}^{ROW}} \right) - 1$$

$$= \left[ \left( 1 - \frac{X_{g,t_2}^c}{X_{g,t_2}^W} \right) - \frac{X_{g,t_1}^{ROW}}{X_{g,t_1}^W} \right] \frac{X_{g,t_1}^W}{X_{g,t_1}^{ROW}}$$

$$= \left[ \left( 1 - \frac{X_{g,t_2}^c}{X_{g,t_2}^W} \right) - \left( 1 - \frac{X_{g,t_1}^c}{X_{g,t_1}^W} \right) \right] \frac{X_{g,t_1}^W}{X_{g,t_1}^{ROW}}$$

which implies that

$$r_g = - \left( \frac{X_{g,t_2}^c}{X_{g,t_2}^W} - \frac{X_{g,t_1}^c}{X_{g,t_1}^W} \right) \left( \frac{X_{g,t_1}^W}{X_{g,t_1}^{ROW}} \right)$$

(22) $r_g = - \left( \frac{X_{g,t_2}^c}{X_{g,t_2}^W} - \frac{X_{g,t_1}^c}{X_{g,t_1}^W} \right) \left( \frac{X_{g,t_1}^W}{X_{g,t_1}^{ROW}} \right)$

Finally, substituting (22) into (20) the index, representing the percent change in country $i$’s exports of $G$, is defined as

(23) $\text{Index} = - \sum_{g \in G} \left( \frac{X_{g,t_2}^c}{X_{g,t_2}^W} - \frac{X_{g,t_1}^c}{X_{g,t_1}^W} \right) \left( \frac{X_{g,t_1}^W}{X_{g,t_1}^{ROW}} \right) \sum_{g' \in G} X_{g',t_1}^{i'}$.
Appendix II: Estimation

Our goal is to estimate expected values \( V^i_t \) and the moving cost parameter \( C^{ij}_t \). We construct a log-linear expression for flows, \( m^{ij}_t \), which can be estimated with Poisson pseudo-maximum likelihood using standard statistical software.

Asymptotically, the total number of agents in sector \( i \) who choose sector \( j \) is equal to \( y^{ij}_t \).

Equation (5) can be expressed as:

\[
\begin{align*}
        y^{ij}_t &= \exp \left\{ \frac{\beta}{\nu} \tilde{V}^{ij}_{t+1} - \frac{\beta}{\nu} \tilde{V}^i_{t+1} - \frac{1}{\nu} C^{ij}_t + \log \left( L^i_t \right) - \frac{1}{\nu} \Omega^i_t \right\}.
        
    \end{align*}
\] (24)

We interpret the equation above as Poisson pseudo-maximum likelihood. Then, the equation (24) becomes the first stage regression equation:

\[
\begin{align*}
        y^{ij}_t &= \exp \left( \Gamma^i_t + \Lambda^j_t + 1_{i \neq j} \delta^{ij} + \epsilon^{ij}_t \right).
        
    \end{align*}
\] (25)

where the destination fixed effect is:

\[
\Lambda^j_t = \frac{\beta}{\nu} E_t V^j_{t+1} - \frac{\beta}{\nu} E_t V^1_{t+1},
\]

the switching cost term is:

\[
\delta^{ij} = -\frac{1}{\nu} C^{ij}_t,
\]

and the origin fixed effect is:

\[
\Gamma^i_t = -\frac{\beta}{\nu} E_t V^i_{t+1} - \frac{1}{\nu} \Omega^i_t + \log \left( L^i_t \right) + \frac{\beta}{\nu} E_t V^1_{t+1}.
\]
Note that the option value term $\Omega^i_t$ can be written as:

$$\frac{1}{\nu} \Omega^i_t = -\Lambda^i_t - \Gamma^i_t + \log(L^i_t).$$

Equation (25) implies a PPML orthogonality condition. We pin down parameters $\Lambda^j_t$, $\Gamma^j_t$ and $\delta^{ij}$ by solving the following orthogonality condition equation (26)

$$\sum_i \sum_j \sum_s \left[ y_s^{ij} - \exp(x_s^{ij} \psi^{ij}_t) \right] \psi_t^{ij} = 0,$$

where $\psi_t^{ij}$ is the vector of parameters for observation $(i, j, t)$ and $x_t^{ij}$ is the vector of data such that $y_t^{ij} = \exp(x_t^{ij} \psi_t^{ij}) + e_t^{ij}$ as in equation (25). Since it is possible to take the derivative of orthogonality condition (26) analytically, PPML estimation is computationally convenient compared to its alternatives.

Note that we could alternatively use a maximum likelihood estimator based on equation (24), rather than PPML, to pin down $\Lambda^j_t$ and $\delta^{ij}$. The alternative MLE estimator based on the objective function $\log \mathcal{L} = \sum_i \sum_j y_t^{ij} \log(m_t^{ij})$ is equivalent to the PPML estimator (proof available upon request). See Artuç (2013) for the Monte-Carlo simulations and further details.
Figures and Tables

Table 1. Simulation Parameters

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<th>Sector</th>
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<td>0.000</td>
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| **Brazil** | | | | | | | | |
| Wage Bill | 0.431 | 0.216 | 0.489 | 0.316 | 0.439 | 0.439 | 0.513 | IO table 2005, IBGE |
| Wage (for) | 1.562 | 1.947 | 1.218 | 1.087 | 0.925 | 0.763 | 1.239 | HH Surveys, PME 2007-2011 |
| Wage (inf) | 0.521 | 1.102 | 0.718 | 0.607 | 0.708 | 0.511 | 1.092 | HH Surveys, PME 2007-2011 |
| Labor (for) | 0.001 | 0.003 | 0.075 | 0.019 | 0.066 | 0.016 | 0.173 | HH Surveys, PME 2007-2011 |
| Labor (inf) | 0.002 | 0.000 | 0.033 | 0.027 | 0.053 | 0.012 | 0.120 | HH Surveys, PME 2007-2011 |
| Consumption | 0.021 | 0.000 | 0.244 | 0.000 | 0.050 | 0.053 | 0.428 | IO table 2005, IBGE |
| Output | 0.027 | 0.017 | 0.255 | 0.074 | 0.093 | 0.039 | 0.494 | IO table 2005, IBGE |
| Exports | 0.010 | 0.015 | 0.122 | 0.000 | 0.000 | 0.000 | 0.000 | IO table 2005, IBGE |
| Imports | 0.002 | 0.018 | 0.088 | 0.000 | 0.000 | 0.000 | 0.000 | IO table 2005, IBGE |

| **Mexico** | | | | | | | | |
| Wage Bill | 0.176 | 0.130 | 0.338 | 0.406 | 0.241 | 0.271 | 0.384 | IO table 2003, INEGI |
| Wage (for) | 0.723 | 1.730 | 0.994 | 1.206 | 0.896 | 0.827 | 1.515 | HH Surveys, ENOE 2005-2011 |
| Wage (inf) | 0.527 | 0.889 | 0.787 | 0.955 | 0.898 | 0.889 | 1.164 | HH Surveys, ENOE 2005-2011 |
| Labor (for) | 0.005 | 0.005 | 0.057 | 0.008 | 0.036 | 0.011 | 0.121 | HH Surveys, ENOE 2005-2011 |
| Labor (inf) | 0.077 | 0.001 | 0.042 | 0.040 | 0.084 | 0.026 | 0.092 | HH Surveys, ENOE 2005-2011 |
| Consumption | 0.028 | 0.000 | 0.249 | 0.000 | 0.116 | 0.042 | 0.366 | IO table 2003, INEGI |
| Output | 0.022 | 0.045 | 0.223 | 0.123 | 0.129 | 0.034 | 0.425 | IO table 2003, INEGI |
| Exports | 0.005 | 0.024 | 0.177 | 0.000 | 0.000 | 0.000 | 0.000 | IO table 2003, INEGI |
| Imports | 0.008 | 0.001 | 0.241 | 0.000 | 0.000 | 0.000 | 0.000 | IO table 2003, INEGI |

Note: Other parameters used in the simulations include the estimated sector-specific entry costs reported in Table 3. Moreover, the calculation of the entry costs (after estimation) required the use of two parameters that come from Artuc et al (2010), namely the discount factor $\beta$ of 0.95 and $\nu$ equal to 0.6.
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### Table 3: Entry Costs

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*z*-statistic in parenthesis.
Figure 1: China’s exports and imports
Source: WITS, mirror data

Figure 2: Export Similarity Index
Number of Manufacturing Goods under Threat Between 1 and 2001 in USA, EU and World Market

USA

EU

World

--- Brazil --- Argentina --- Mexico

Source: WITS, HS Rev. 3, 4-digits
Direct or Strong Partial Threat

% of Manufacturing Exports under Threat Between 1 and 2001 in USA, EU and World Market

USA

EU

World

--- Brazil --- Argentina --- Mexico

Source: WITS, HS Rev. 3, 4-digits
Direct or Strong Partial Threat

Figure 3: DRCA
Figure 4: Exports to China
Figure 5: China’s Direct Effect: Mining
Figure 6: China’s Direct Effect: Agriculture
Figure 7: China’s Direct Effect: Manufacturing
Figure 8: Employment Distribution: Argentina
Figure 9: Total Employment: Argentina
Figure 10: Wages: Argentina
Figure 11: Employment Distribution: Brazil
Figure 12: Total Employment: Brazil
Figure 13: Wages: Brazil
Figure 14: Employment Distribution: Mexico
Figure 15: Total Employment: Mexico
Figure 16: Wages: Mexico