Trade-Induced Local Labor Market Shocks and Asymmetrical Income Risk*

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June, 2019

Abstract

This paper investigates empirically the relationship between international trade and inequality in Brazil. In particular, we inspect how exogenous supply and demand shocks affect labor income risk in different regions between 2000 and 2012. Using a longitudinal administrative data set, we find considerable regional heterogeneity in the second and higher moments of the individual income growth distribution. Then, exploiting initial regional sectorial composition, we evaluate the impact of the increase in the Brazil-China trade flows on the dispersion, asymmetry and tails of these distributions. Results indicate that Chinese imports increase the dispersion of income risk. This effect is asymmetrical, since part of the effect comes from the growth of permanent negative shocks relatively to positive ones. The welfare losses of such an increase in risk can be substantial. Through the lens of an incomplete market model, an unborn individual would be willing to forgo up to 12.43% of his consumption to not be part of this riskier labor market.

JEL Codes: D31, E24, F14, F16, J31.
Keywords: Labor Income Risk, International Trade, China Shock, Income Process.

*We thank Jan Stuhler, Andrés Erosa, Matthias Kredler, and Felix Wellschmied for the helpful comments and suggestions. Martinez acknowledges financial support by grant ECO2014-56676-C2-1-P from the Spanish Ministry of Economy and Business. Mello acknowledges financial support from the Spanish Ministry of Education and Culture. All errors are ours.

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1 Introduction

One of current pressing economic questions is how economies adjust to changes in international trade. Although early theoretical work points that openness to trade is bound to increase welfare, present evidence has shown that the adjustment can be long and potentially costly for certain groups of individuals. In particular, empirical work have shown that international trade can have first order effects on the average income, employment level and labor force participation of affected regions[1]. Nevertheless, while a lot is known about the impact on the income *level*, few studies focus on the impact on income risk - the distribution of income *changes*[2].

This paper aims to shed light on the effects of international trade on the idiosyncratic income risk faced by the workers. It is easy to rationalize how a riskier labor market can have pervasive consequences to the individual welfare - even when average wages are unchanged. First, economic shocks and unexpected income changes often have persistent effects. Jacobson et al. (1993) shows that displaced workers have lower wages even 5 years after displacement. Second, in the presence of borrowing constraints, unexpected income changes are one of the main drivers of welfare and consumption inequality.

There might be several reasons why international trade is linked to idiosyncratic income changes. Increase in the exposure to trade induces reallocation of labor within and across industries, sometimes associated to long unemployment spells and loss of human capital (Dix-Carneiro (2014)). Further, firms endogenously respond to changes in the international markets by opening and closing plants (Cosar et al. (2014)). As far as *ex-ante* similar workers follow different labor market trajectories in response to those events, changes in the trade flows can affect the distribution of idiosyncratic economic shocks. On top of the effects from the reallocation of workers, which tend to be transitory, higher integration with international markets can increase *permanently* income risk. To the extent integrated markets have a higher degree of pass-through from the shocks of the global economy to the local demand of labor, an increase in trade can leave labor income more exposed to changes in the international environment. In addition, even after the economy have adjusted to the trade shocks, the permanent shift in sector and occupation composition might leave the labor market more or less risky.

Our analysis uses Brazilian data to understand the impact of trade on risk. Brazil has been widely regarded as an ideal country to study trade shocks. First, it experienced a

[1]For instance Autor et al. (2013) and Dix-Carneiro and Kovak (2017).

[2]Notable exceptions are Krishna et al. (2014) and Krebs et al. (2010)

variety of changes in its trade dynamics, from the trade liberalization of the early 90's to the more recent commodity-manufactures trade boom with China in the 2000's. Second, its sheer size, combined with various natural resources and divergent human capital accumulation, provides a large number of local labor markets with different comparative advantages that may be subject to heterogeneous trade shocks. In the spirit of Autor et al. (2013) and Costa et al. (2016), we exploit the increase in the Brazil-China trade volume between 2000 and 2012 at the national level, together with local industry composition, to construct variation across time and space of the impact of the "China shock" in the Brazilian labor market. Our identification approach relies on within local labor market changes in trade exposure, effectively comparing changes of labor income risk of regions affected by trade with regions that have been somewhat untouched by it. Yet, as in much of the literature, the shift-share estimates would be biased if there are time and region-varying unobserved factors correlated with both the Brazilian labor market and the increase in trade with China, such as sector specific productivity growth or changes in demands for certain goods due to rise in income. Therefore, we use variation in the trade flows of China with the rest of the world (excluding Brazil) to create instruments for the Brazil-China imports and exports. To the extent that the Chinese trade flows with the rest of the world is unrelated to the Brazilian labor market, these are valid instruments.

To construct measures of labor income risk at fine defined local labor markets, we use longitudinal administrative labor data that covers the universe of formal workers in Brazil. In particular, we construct the distributions of $n-$years income changes using the residual income of workers that have not moved out of their regions. Given the recent focus of non-normal income growth highlighted by Guvenen et al. (2019), our examination is not limited to the variance but also focus on the asymmetry and tails of the distribution. Guided by a region-specific stochastic income process, we interpret the moments of income changes over long and short time horizon as persistent and transitory income shocks.

The empirical results can be summarized as follows. The increase in imports from China is associated with an increase in the dispersion in both the long and short time horizon distribution of income growth. This effect is robust and economically strong. Suppose we rank all regions by their income growth dispersion in 2005. In our preferable specification, an increase in imports of US$ 1000 per worker is sufficient to bring a region in the 25th centile to the 50th centile in the rank dispersion risk. There is no evidence that an increase in the exports to China leads to changes in the dispersion of the labor income risk. In the case of the higher moments, Chinese imports are associated to an increase in the negative income changes in the 5-year distribution, as well as the increase in the kurtosis in the 1-year income growth distribution. Again, the impact of Brazilian exports to China in both the asymmetry and tails is minimal. Finally, we estimate that an increase in imports of US$ 1000 per worker can decrease the average yearly income up to 25%.

Afterwards, we quantify the welfare cost given by the increase in labor income risk from the "China shock". To tackle this question, we estimate two stochastic income processes: one targeting the empirical moments before the increase in trade flows, and the other targeting the counterfactual moments implied by our causal estimates. We input our estimates into an off-the-shelf incomplete markets model and compute the utility losses of being in the riskier labor market. We found that an unborn individual would be willing to forgo up to 12.43% of his consumption to not be part of this labor market. When decomposing the sources of the increase in risk, results show that the utility losses come mainly from the increase in dispersion. This is because the impact of trade on the higher moments is relatively small relative to the dispersion, and its effects are transitory, making them easy to insure and lowering their welfare influence.

Related Literature

Our paper contributes to different strands of the economic literature. Broadly, it contributes to the vast literature of the impact of trade shocks on local labor markets. Our work relates closely to the empirical literature on the labor market effects of the increase of Chinese trade-flows with the rest of the world established by the seminal paper of Autor et al. (2013)[3]. In the case of Brazil, the "China shock" had two tales: on one hand some regions received an import competition shock from China, on the other, different places have increase their exports to China. Costa et al. (2016) found that the export demand shock is associated with higher growth in wages over 2000 to 2010, while the import supply shock is related to lower wage growth in manufacturing workers. They did not observe any effect on employment, though their estimates are somewhat noisy. In the Brazilian context, other papers have studied the impact of trade in the local labor markets, more specifically exploiting the decrease in tariffs in the 90s. Kovak (2013) provides an intuitive way to formalize national level changes prices through local level wages. Dix-Carneiro and Kovak (2019) studies the margin of adjustments after the trade liberalization, they focus on workers switching between regions, industries and formal status. None of this papers have looked at changes in the labor income risk.

[3]See Autor et al. (2016) for a review.

A large body of the economic literature has investigated the changes in the dispersion of the labor income risk in various context. Storesletten et al. (2004b) argues that the dispersion of the idiosyncratic risk is strongly countercyclical, while Karahan and Ozkan (2013) studies the dispersion in the life-cycle. For a survey see Meghir and Pistaferri (2011). More recently, following Guvenen et al. (2019) and Arellano et al. (2017), an incipient literature has shifted its focus to the non-normality of earnings risk distribution. Busch et al. (2018) pointed that the skewness of the earnings growth distribution displays strong procyclical fluctuations in the U.S., Germany and Sweden. Using German data, Sanchez and Wellschmied (2017) focus on the asymmetry of the earnings shock during the life-cycle. In the case of Brazil, Gomes et al. (2019) have shown that the non-normal income growth is also present in the context of workers changing between informality status. Nevertheless, because of data limitations, they center their analysis on the 1-year income growth distribution. To the best of our knowledge, we were the first to exploit the individual distribution of income growth at local labor markets to infer changes in earning risk.

Finally, few studies have investigated the effect of trade on labor market risk. Krebs et al. (2010), using Mexican data, decomposes measures of earnings risk at the industry level and exploits change in tariffs to calculate the effect of trade policy on risk. They found that a change in tariffs, in highly protected industries, is associated to an increase in the variance of the persistent shock, and interpret these results as evidence of the short run impact of trade policy changes on income risk. For the U.S., Krishna and Senses (2014) estimates the persistent risk by industry in three different periods and specify a time and industry fixed effect model to identify the effect of import penetration in the variance of the idiosyncratic risk. Both of them have used relatively short panels (two and three years, respectively) and have aggregated workers at the industry level, missing a large part of the population that works in the non-traded sector. Our paper differs from theirs by (i) looking into higher moments, (ii) exploit variation within local labor markets, and (iii) use a longer panel which is more informative about the persistent innovations.

2 Region-specific Idiosyncratic Risk

The literature on income dynamics has traditionally dedicated most of its attention on labor income risk over the time and over the life-cycle. To formalize our analysis on the idiosyncratic labor income risk of various local labor markets, we present a simple but flexible stochastic income process that accounts for both time-varying and region specific distributions of economic shocks, and allow workers move across regions. Let $y^i_{r,t}$ be the log yearly residual earnings of a worker i at year t in local labor market r:

$$\begin{aligned} y^i_{r,t} &= \alpha^i + z^i_{r,t} + \varepsilon^i_{r,t} \\ z^i_{r,t} &= \rho z^i_{k,t-1} + \eta^i_{r,t} \\ \eta^i_{r,t} &\sim F_\eta(m_\eta(r,t)) \\ \varepsilon^i_{r,t} &\sim F_\varepsilon(m_\varepsilon(r,t)) \\ \alpha^i &\sim F_\alpha(m_\alpha(r,t)). \end{aligned} \tag{1}$$

Where $F_x(m_x(r,t))$ denotes a general distribution F_x with mean 0 and a vector of moments $m_x(r,t)$, possibly region and time-specific, characterizing the distribution. The econometric model includes a persistent component modelled as an AR(1) process with iid innovations η^i_t drawn from a distribution F_η and an iid transitory innovation ε^i_t drawn from a distribution F_ϵ. For completeness, we also include a fixed effect α^i.

As usual, the income of a worker i at time t will be represented by the fixed effect α^i, the transitory shock $\epsilon_{r,t}$ received in time t, and the history of accumulated persistent shocks given by $z_{r,t}$. The key difference between the usual process specified in the literature, with the one from equation 1, is that individuals may switch from region k to region r from time $t-1$ to time t. For simplicity, we abstract from modelling additional income shocks to the switchers, nor specifying the moving probabilities.

2.1 Inferring Risk from Individual Income Growth and Local Labor Market Shocks

Given the stochastic process specified in 1, one can show that distribution of income growth of short and long-horizons can be informative on the magnitude of the transitory and persistent shocks[4]. For simplicity, let us set the persistence of the AR(1) to $\rho = 1$, effectively making the shock η^i_t fully permanent. Then, let us define the income growth from $t-n$ to t of an individual with region history $\mathbf{r} = \{r_0, r_1, ..., r_n\}$, where r_0 represents the most recent region and r_n the region at time $t-n$, as $\Delta^n y^i_{\mathbf{r},t} = y^i_{r_0,t} - y^i_{r_n,t-n}$. Then, we can write it as:

[4]The usual identification argument in the income dynamics literature relies on the variance-covariance matrix in differences as in Blundell et al. (2008) (or in levels as in Storesletten et al. (2004a)). In the Appendix C.2, we show that this is equivalent of using the $n-$time variance.

$$\Delta^n y^i_{\mathbf{r},t} = \sum_{k=0}^{n-1} \eta^i_{r_k,t-k} + \varepsilon^i_{r_0,t} - \varepsilon^i_{r_n,t-n}. \tag{2}$$

Further, defining the moments $m_x(r,t) = [\sigma^2_x(r,t), \mathcal{S}_x(r,t), \mathcal{K}_x(r,t)]$ of the distribution $F_x(m_x(r,t))$, where σ^2_x is defined as the variance, $\mathcal{S}_x$ is the third central moment and $\mathcal{K}_x$ is the fourth central moment[5]. We can write the variance of $\sigma^2(\Delta^n y_{\mathbf{r},t})$ as a function of the variances of F_η and F_ϵ:

$$\sigma^2(\Delta^n y_{\mathbf{r},t}) = \sum_{k=0}^{n-1} \sigma^2_\eta(r_k, t-k) + \sigma^2_\epsilon(r_0, t) + \sigma^2_\epsilon(r_n, t-n). \tag{3}$$

In appendix C.1, we derive similar expressions for the third central moment, $\mathcal{S}(\Delta^n y_{\mathbf{r},t})$, and the fourth central moment, $\mathcal{K}(\Delta^n y_{\mathbf{r},t})$. Equation 3 shows that as individual idiosyncratic shocks accumulate over time, the variance of $\Delta^n y_{\mathbf{r},t}$ increases with n. A similar argument can be made for $\mathcal{S}(\Delta^n y_{\mathbf{r},t})$ and $\mathcal{K}(\Delta^n y_{\mathbf{r},t})$. Moreover, it shows that is not enough to pool workers by the same time periods. To be able to differentiate region-specific distributions, the moments of the income growth distribution have to be calculated for workers with *the same* location history $\mathbf{r}$. Leaving together workers with different location history hinder the trace of the original region of the shock. On top of that, the income growth of movers is inherently different than stayers, and its shocks are likely to depend on both the original and new region. Nevertheless, as the time horizon grows large, the number of possible histories increases exponentially and the number of individuals used to compute the income growth distribution potentially becomes very small. Since we are particularly interested in the idiosyncratic risk of an arbitrary region, equation 3 naturally points to look directly to the labor income dynamics of workers who have not moved out of their original labor market, motivating us to look only to the ones who have not moved out. From now on, we consider only histories where workers stay in one region $\mathbf{r} = \{r_1, .., r_n\} = \{r, ..., r\}$.

The next step is to understand how aggregate economic conditions (e.g. say the level of trade volume) of the local labor market r affects the distributions of idiosyncratic income changes (e.g. idiosyncratic risk). To facilitate exposition, let us go through an example.

[5]We decided to use the central moments instead of the standardized skewness and kurtosis to abstract from the effect on the variance.

Suppose we observe a number of regions r for 5 periods, such that we can construct the distributions of $\Delta^n y^i_{r,t}$ for $n = 1, ..., 4$ and region-specific economic conditions $Z_{r,t}$ for every t. A regression of $\sigma^2(\Delta^4 y_r)$ on $Z_{r,t}$ yields the elasticity of the level of the economic condition on the volatility of the distribution of 4-year income changes. Nevertheless, in the case that the distributions of idiosyncratic shocks $(F_\eta(t-1), ..., F_\eta(t-k))$ are orthogonal to future economic conditions $(Z_t, Z_{t+1}, ..., Z_{t+k})$, the coefficient of the regression on $\sigma^2(\Delta^4 y_r)$ on $Z_{r,t-k}$ can be informative on whether the idiosyncratic shocks are persistent or transitory. Using the example of Z_t and Z_{t-2}:

$$\sigma^2(\Delta^4 y_t) = \underbrace{\overbrace{\sigma^2_\eta(t) + \sigma^2_\epsilon(t)}^{\text{Affected by } Z_t} + \sigma^2_\eta(t-1) + \sigma^2_\eta(t-2)}_{\text{Affected by } Z_{t-2}} + \sigma^2_\eta(t-3) + \sigma^2_\epsilon(t-4). \tag{4}$$

Obviously, the assumption that the distribution of individual income shocks are orthogonal to future economic conditions is extreme and implausible given that Z_t and Z_{t-2} are likely autocorrelated. Still, even in the presence of some autocorrelation, a higher coefficient of Z_{t-2} than Z_t can be indicative that changes in the aggregate conditions have impact on the permanent distribution of shocks.

One concern is that the effect of Z_t on the contemporaneous distributions $\sigma^2_\eta(t)$ and $\sigma^2_\epsilon(t)$ is different than the effect of Z_{t-2}[6], so they are not directly comparable. In this case, one could gather evidence on the long and short run effects on the contemporaneous distribution by regressing Z_t and Z_{t-2} on $\sigma^2(\Delta^1 y_t)$ instead. Thus, by running multiple regression on both short and long run income changes (e.g. $\Delta^1 y_t$ and $\Delta^4 y_t$) and contemporaneous and lags of the aggregate economic condition (e.g. Z_t and Z_{t-2}) one could construct evidence of the impact of Z_t on the distributions of permanent and transitory idiosyncratic shocks.

Lastly, it should be pointed that although the income process is a useful starting point to disentangle persistent from transitory shocks, we acknowledge that income growth are not only driven by unexpected changes but also by individual choices. Unfortunately, to separate decisions from unexpected income changes it requires either additional data or structure (e.g. an economic model). Although this is a interesting question to be pursued, it is out of the scope of this project.

[6] The impact of Z_t on the distribution of time t can be higher than Z_{t-2} if the aggregate in the idiosyncratic distribution is felt right away, but also possibly lower in the case that the effect of Z takes time to unfold.

3 Data

This paper uses data from three different sources. First, we use a Brazilian matched employer-employee panel data from 1996 to 2012, RAIS (*Relação Anual de Informações Sociais*). It contains all employment spells of the universe of workers of the Brazilian formal sector, including average gross monthly wages and selected individual characteristics. Workers are identified across years using their anonymized social security number. This dataset is of restricted use only and is made available by the Ministry of Labor upon approval of research projects.

We aggregate all the employment spells and compute the yearly labor income in the formal sector for all workers. Then, we assign the worker a 5-digit industry code and a municipality based on the longest employment spell of a given year. Our sample restriction is standard in the literature. To alleviate concerns that individuals may be taking human capital and retirement decisions, we select workers between 25 and 55 years old that had positive earnings in the given year. Our largest concern about the data is that it only covers formal employers. Brazil has a large informal sector and previous evidence have pointed that trade shocks might affect the degree of informality of local markets[7]. If that is the case, the selection of workers into informality changes across time and regions and it is correlated with the trade shocks which could bias our estimates. To overcome this issue, we select our sample to individuals observed in 2000 and follow the ones highly attached to the formal labor market, restricting the ones to be observed a minimum number of years in the the 1999-2012 period. There is a clear trade-off with this approach. The higher the number of years we restrict the worker to be observed, the more stable is our sample and less prone to be impacted by changes in informality. Nevertheless, imposing too many years employed, may miss important unemployment dynamics, specially scaring effects of being one year out of the formal market, dampening the observed income risk. In the end, we found 7 years a good balance between this trade-off.

The data on international trade comes from the United Nations COMTRADE database. This is publicly available data at the commodity level of bilateral trade between countries. We gather data of imports and exports of each country with the rest of the world (aggregate) and with Brazil. This paper uses data from 2000 to 2015 at the 6-digit Harmonized System level (HS6), converted to 2015 U.S. dollars using CPI. The empirical strategy requires the matching between commodity-level trade data with the sector-level (CNAE

[7] Costa et al. (2016) and Dix-Carneiro and Kovak (2019).

1.0[8]) data available at RAIS. Therefore, we create a mapping by aggregating the more detailed commodity data into traded sectors. We are left with 76 traded sectors, including 18 agricultural sectors, 8 extractive sectors and 50 manufacturing sectors (table A.2, in the appendix).

Finally, we use data from the Brazilian Census of 2000. This is publicly available and comes from the Brazilian Institute of Geography and Statistics. This data is used to create industry and microregion-level measures of labor force, which in turn are used to construct the industry shares and region weights. Our unit of analysis is the microregion as defined by the Brazilian statistical agency, a set of municipalities that are connected through a relation of dependence and displacement of the population in search of goods, services and work. We refer to it as microregion, local labor market, or regions interchangeable to avoid repetition.

4 Trade and Income Growth in Local Labor Markets

4.1 The China Shock in Brazil

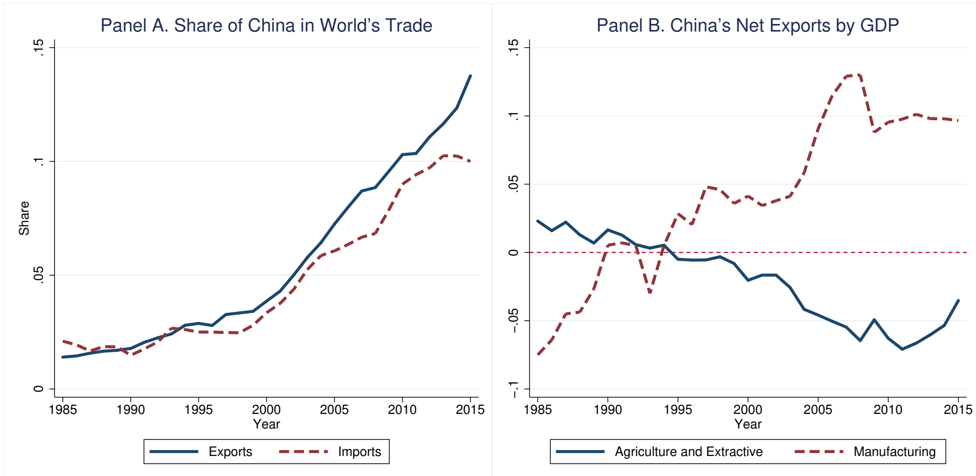
Since the trade behavior of countries and companies are intertwined and jointly determined by decisions' of their trade partners, identifying the impact of trade shocks on local labor markets poses substantial empirical challenges. In this context, the rapid rise of China into the leading trade nation[9] and second largest economy in the world offered a remarkable opportunity to circumvent the identification concerns of applied economists.

As carefully described in Autor et al. (2016), there are some features of the *China rise* that makes it particularly interesting for the study of the causal effects of trade. The first one is its unexpected nature. In spite the implementation of numerous reforms following Mao's death in 1976, the Chinese trade expansion did not began until the early 1990s, as seen in Figure 1 Panel A. The instability and skepticism following the events at Tiananmen Square in 1989, made it difficult to anticipate the impressive performance of the Chinese economy in the decades to follow. Second, the substantial degree of the Chinese isolation during the decades of the Maoist era created an enormous opportunity for future catch up. Between 1952 and 1978, China's GDP Per Capita went from the 59th position in the

[8]CNAE stands for *Classificação Nacional de Atividades Econômicas* and it is similar to other international classifications, such as NAICS and SIC.

[9]According to the WTO, in 2014, China was the world's largest merchandise trader, with combined exports and imports worth USS 4,303 billion. The United States was close behind in second place, with total trade worth USS 4,032 billion.

Figure 1: The rise of China in international markets



Notes: Panel A plots the share of Chinese participation in the world's merchandise trade. Panel B plots Chinese net exports (total exports minus total imports) divided by its GDP. Source: WTO (http://data.wto.org/).

world to the 134th[10]. Thus, China's astounding growth from the beginning of 1990s was largely explained by its accumulated productivity gap with the developed world.

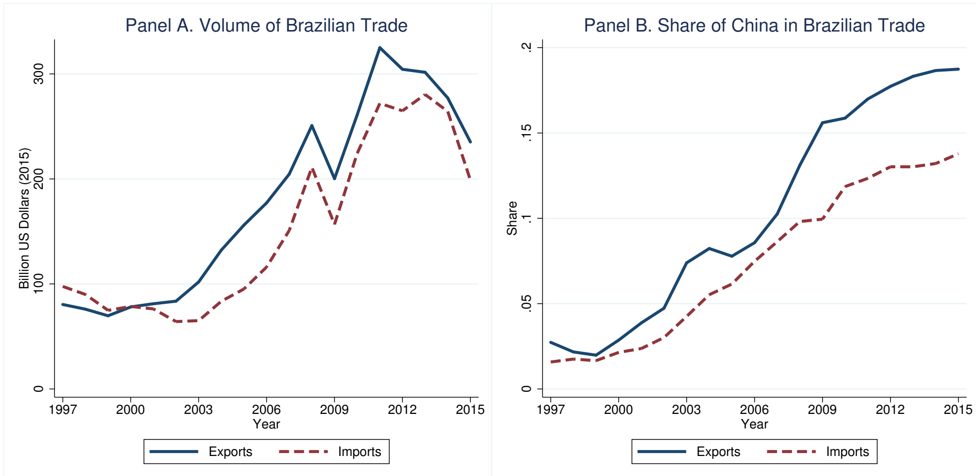
Third, China's comparative advantages created trade shocks of a specific pattern that differentially affected countries and local labor markets, according to their previous sectorial specialization. Figure 1 Panel B shows the Chinese comparative advantage in the production of manufacturing goods. From 1994 to 2010, China's net exports in the manufacturing sector in percentage of GDP grew from zero to ten percent, having reached its peak in 2008, with 13 percent. In contrast, during the same period, China's net exports in the agriculture and extractive sector went from zero to negative 6 percent of the GDP. This trade concentration in labor intensive sectors can be partially attributed to the migration of 250 million workers from farms to cities, following the decollectivization of the Chinese agricultural sector, and the closure of state-owned enterprises (Autor et al., 2016).

Although the Chinese trade expansion started in the early 1990s, it accelerated substantially in the 2000s (Figure 1, Panel A). In 2001, China joined the World Trade Organization (WTO), implementing a series of changes in favor of trade liberalization. These included, but are not limited to privatization of state-owned enterprises and the end of restrictions that obliged companies to export through state intermediaries.

During a similar time-period as the *China rise*, Brazil also expanded its volume of

[10]Penn World Tables 8.0, in constant national prices (2005).

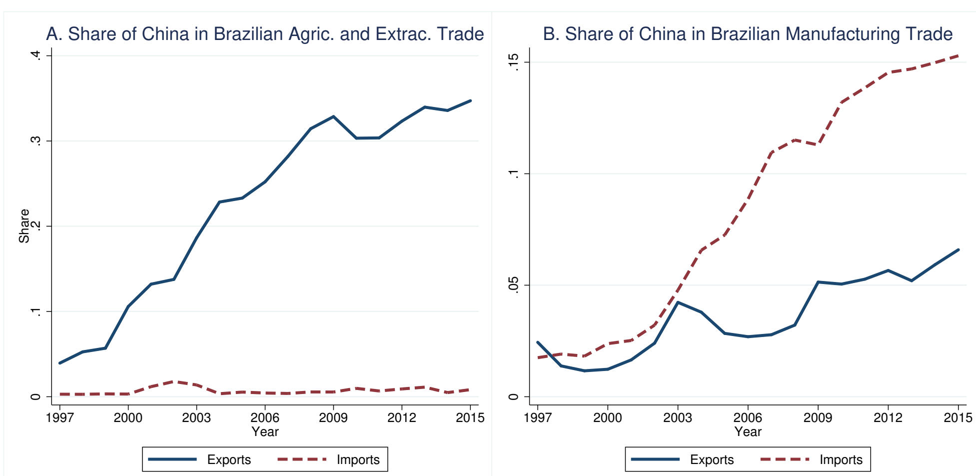
Figure 2: Brazilian imports and exports over time



Notes: Panel A plots the volume of Brazil's international trade in billion of 2015 US dollars adjusted by CPI. Panel B plots the Chinese participation in the Brazilian trade. Source: UN COMTRADE Database.

trade, as portrayed in Figure 2 Panel A. Simultaneously, the importance of China as a trade partner for Brazil increased significantly. In Figure 2 Panel B, we see that the share of Chinese participation in Brazilian exports went from 2.7% in 1997 to 15.9% in 2010, and from 1.6% to 11.9% for Brazilian imports.

Figure 3: Share of China in Brazilian imports and exports by sector



Notes: Panel A plots the Chinese participation in Brazilian agricultural and extractive trade. Panel B plots the Chinese participation in Brazilian manufacturing trade. Source: UN COMTRADE Database.

The increase in the Chinese participation in international trade, combined with its comparative advantages, culminated into a large global supply shock of manufacturing goods and a large global demand shock of agricultural and extractive products. This pattern of specialization affected the Brazilian economy in a particular way. In Figure 3, we plot the share of Chinese participation in the Brazilian exports and imports by sector. The Chinese participation in Brazilian exports went from 3.9% to to 34.7%, from 1997 to 2015, in the agriculture and extractive sectors (Panel A), and from 2.4% to 6.6% in manufacturing. In contrast, it went from 1.8% to 15.3% in imports of manufacturing, while it stayed around zero in imports of agricultural or extractive goods.

Thus, in Brazil (and in other commodities-based economies), the *China rise* provoked both negative supply shocks in the manufacturing sector, due to the the Chinese competition, and positive demand shocks in the agriculture and extractive sectors, due to the increase in the Chinese consumption of raw products. In order to study how much exports and imports affected the local labor markets, we define the following measures for import (IS_{rt}) and export (XD_{rt}) penetration:

$$XD_{rt} = \frac{1}{L_{r,2000}} \sum_j \frac{L_{rj,2000}}{L_{Bj,2000}} V_{BjC,t} \tag{5}$$

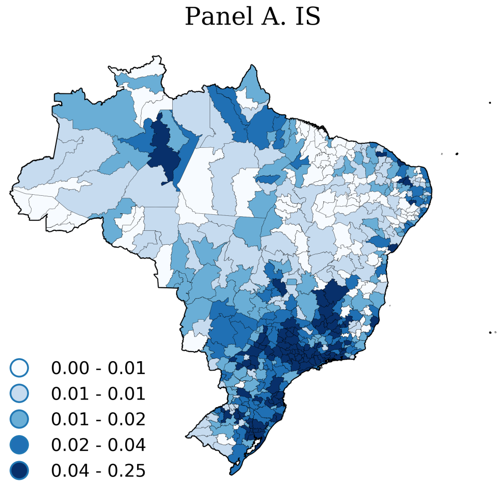
$$IS_{rt} = \frac{1}{L_{r,2000}} \sum_j \frac{L_{rj,2000}}{L_{Bj,2000}} V_{CjB,t} \tag{6}$$

where j represents sector; B represents Brazil; and r the microrregion. The terms $V_{BjC,t}$ and $V_{CjB,t}$ denote the value of Brazil's exports to and imports from China. The variable $L_{rj,2000}$ is defined as the size of the workforce in sector j within microregion r, while $L_{Bj,2000}$ and $L_{r,2000}$ are the Brazil wide work-force in sector j and the total workforce in microregion r, all measured in 2000. The construction of these variables follows the broad literature of Bartik-type instruments use interactions of initial local shares with national growth rates[11]. Both IS_{rt} and XD_{rt} are measured in thousands of dollars per worker

Figure 4 plots the average yearly change in the import and export penetration ($\Delta IS_{rt} \equiv IS_{rt} - IS_{rt-1}$ and $\Delta XD_{rt} \equiv XD_{rt} - XD_{rt-1}$) from 2000 to 2012 by region in Brazil. At first glance, it seems that the microregions affected by the increase in exports to China, were not the ones affected by the increase in imports from China. This is in fact true, the partial

[11]See Goldsmith-Pinkham et al. (2018) and Borusyak et al. (2018) for a in-depth discussion of the assumptions behind these type of variables.

Figure 4: Distribution of Average Yearly Change of IS_{rt} and XD_{rt} from 2000 to 2012



Notes: The figure plots the average yearly change in imports and exports from 2000 to 2012 by region. Panel A plots $\Delta IS_{rt} \equiv IS_{rt} - IS_{rt-1}$ and panel B plots $\Delta XD_{rt} \equiv XD_{rt} - XD_{rt-1}$. Values are measured in thousands of dollars per worker and are divided by quintiles.

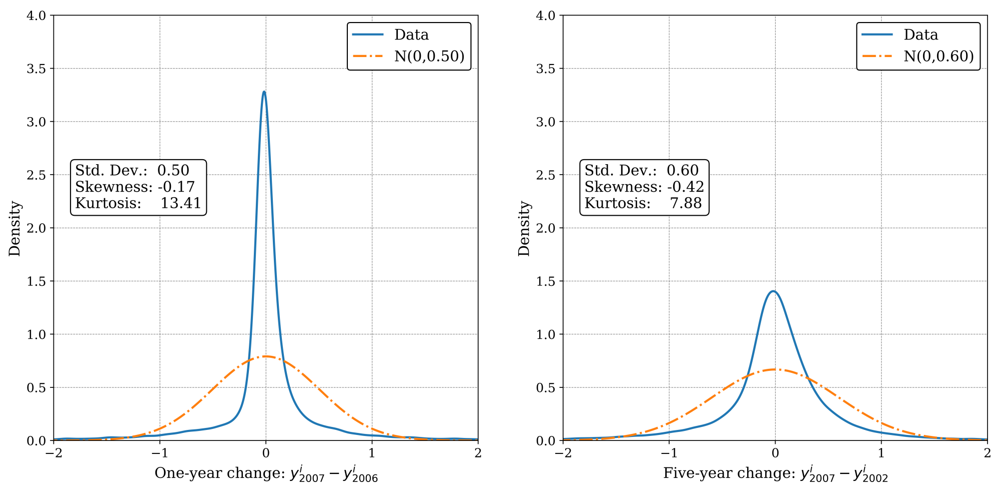
correlation between the changes in ΔIS_{rt} and ΔXD_{rt} is small, as a regression of ΔIS_{rt} on ΔXD_{rt} (weighted by labor force and including year fixed effects) yields a statistically insignificant coefficient of -0.003. This is not surprising given that imports from China were mostly concentrated in manufacturing, such as electronic, machinery and electrical equipment, while exports were mainly accounted by agricultural or extractive, such as nonprecious metals, soy beans and oil and gas.

In terms of the magnitude, the distribution of the shocks are right skewed and masks substantial heterogeneity across regions. The average yearly increase of IS_{rt} in regions less affected was around of 10 dollars per worker, while more affected places received an average increase of between 40 to 250 dollars per worker. In terms of exports the variation is even stronger, as the average yearly increase in XD_{rt} goes from less than 10 dollars to more than 3000 dollars per worker. However, though it seems that the increase in export is larger, it is important to put in perspective the reach of each shock in terms of the overall population. The microregions in fifth quintile of ΔIS_{rt} (the dark regions in the map) cover roughly 48% of the Brazilian labor force, while the microregions in fifth quintile of ΔXD_{rt} accounts for just 15%. Overall, the (weighted) average yearly increase of IS_{rt} and XD_{rt} was about US$49 and US$78 per worker, respectively.

4.2 Trade and Income Growth

In this section, we analyze how the distribution of income growth changes over time and across local labor markets in Brazil and how it correlates with the increasing in import and export penetration. The object of our analysis is the differences of annual log labor income net of age and year effects[12]. Precisely, we define the moment of a local labor market r for period t as $m_{rt}[\Delta^n y^i_{rt}]$, where $\Delta^n y^i_t \equiv y^i_t - y^i_{t-n}$ is defined as the residual earnings growth of individual i between t and $t-n$. In particular, as it was argued in Section 2, we document the moments of $n = 1, 3$ and 5 and interpret the short time horizon as being informative for the transitory and the long horizon for the persistent earnings risk.

Figure 5: Distribution of Log Earnings Changes: One and Five-year changes



Notes: The distribution is computed using 100,000 individuals sampled from the regions in the highest quintile of import penetration. The growth rate is taken between the years of 2007-2006 and 2007-2002. The density is computed using a Gaussian Kernel with bandwidth equal to 0.05.

Our descriptive analysis will have a special focus on the asymmetry and the tails of the income changes distribution. As discussed by Guvenen et al. (2019) and others, the distribution of income growth is asymmetrical and displays a large mass of workers with little income change for one year to another. In figure 5, we show that the asymmetrical leptokurtic distribution is also present in Brazil. The main question is whether changes in these distributions correlates with the increase in trade. In Table 1, we present summary statistics of 1, 3, and 5 years income changes of the distribution of workers in the pre-China trade years (1996-2001) and during the final years of the China shock (2007-2012). Note

[12]More specifically, this is defined as the residual of a regression of log income on age and year dummies.

that the statistics are computed for workers sampled in 2000, thus, differences between the two time periods are also due to age effects. For that reason, our comparison will focus in the difference between the labor markets in the first and fifth quintile of ΔIS_{rt}.

Dispersion

The first step to understand income risk is to look at the dispersion of the distribution of income changes. We report both the variance and a percentile based measure of dispersion, the difference between the 90th and 10th percentiles of the income changes distribution, $P9010$, which is robust to extreme observations. As expected, Table 1 shows that the longer is the time-horizon of income changes, the higher is the dispersion of the distribution.

Regarding the effect of trade, the dispersion clearly decreased from the period pre-China relatively to the period after the trade-shock in all regions[13], nevertheless, regions less affected by import competition have decreased relatively more than the ones more affected, effectively becoming less risky. This effect is robust for both measures of dispersion and shorter and longer horizons. For example, the variance of 1-year income changes of workers in the 1st import penetration quintile decrease from 0.205 to 0.175, around 15%, while for the workers belonging to the 5th quintile, the variance barely change at all, falling from 0.258 to 0.245, a 5% change. In a longer time span the picture remains the same, the variance of 5-years income change of workers in the 1st import penetration quintile decreases more the 38%, from 0.408 to 0.249, while workers in the highest quintile have decreased from 0.457 to 0.350, around 23%.

Also, the variance of workers in the lowest import penetration quintile is already lower than the ones in the highest quintile in 1996-2001, thus, in the period post-China, the distance in income volatility increases even further. We note, however, that the $P9010$ of regions in both quintiles are very similar to each other.

Asymmetry

As argued before, import penetration is positively correlated with dispersion of the distribution of earnings changes. In the case of asymmetry the picture is less clear. We report

[13]Notice, that we select the sample in 2000 and followed the workers up to 2012, thus there is a clear "age-effect". Moreover 2007 to 2012 was a period of high-growth rates for the Brazilian economy.

Table 1: Summary Statistics of Income Changes by 1st and 5th Quintile of Increase in Import Penetration

	$\Delta^1 y_t^i$		$\Delta^3 y_t^i$		$\Delta^5 y_t^i$	
	1st Quintile	*5th Quintile*	*1st Quintile*	*5th Quintile*	*1st Quintile*	*5th Quintile*
			Variance			
1996-2001	0.205	0.258	0.319	0.380	0.408	0.457
2007-2012	0.175	0.245	0.222	0.317	0.249	0.350
			P9010			
1996-2001	0.668	0.694	1.092	1.083	1.334	1.309
2007-2012	0.514	0.658	0.802	0.943	0.955	1.083
			Third Central Moment			
1996-2001	0.000	-0.017	-0.001	-0.006	-0.027	0.018
2007-2012	-0.032	-0.045	-0.021	-0.019	-0.012	-0.014
			Kelley Skewness			
1996-2001	0.263	0.133	0.243	0.098	0.203	0.071
2007-2012	0.163	0.042	0.220	0.097	0.230	0.086
			Fourth Central Moment			
1996-2001	0.528	0.923	0.660	1.260	0.745	1.330
2007-2012	0.473	0.794	0.515	0.996	0.477	0.958
			Crow-Siddiqui Kurtosis			
1996-2001	10.777	12.079	5.695	7.169	4.395	5.583
2007-2012	12.216	13.587	6.613	7.706	5.079	5.892

Notes: To calculate the distribution of income changes, we sample 100,000 individuals in 2000 from regions in the 1st and 5th quintile of the changes in the import IS_{rt}. We compute the yearly average for the statistics with multiple years observations.

both the third central moment, and the Kelley skewness, which is defined as:

$$\mathcal{S}_k = \frac{(P90 - P50) - (P50 - P10)}{(P90 - P10)}. \tag{7}$$

The Kelley skewness has been widely used by the literature for two reasons: (i) it is robust to outliers, since it does not use observations in the top and bottom deciles, and (ii) it provides a quick and intuitive way to decompose overall dispersion in the fraction that is accounted by the upper tail ($P90 - P50$) and the one accounted by the lower tail ($P50 - P10$).

In Table 1, we observe that the third central moment is negative for both regions in the lowest and in the highest quintile of import penetration in most of the cases. In the case of the Kelley skewness, however, all cells are positive. Given that the Kelley do not use observation in the extreme of distribution, we interpret this results as evidence that extreme income changes are larger in the negative tail of distribution. Although, when compared to other countries, the positive Kelley skewness is a somewhat surprising result[14], in the context of Brazil, this result is not unexpected. It is well-known that the asymmetry of the income change distribution is pro-cyclical[15]. In both periods, Brazil experienced positive GDP growth: it had grown an average of 2% per year from 1996 to 2001, and from 2007 to 2012 it grew on average 3.68%[16].

In the context of trade, however, it is not clear whether import penetration correlates with the asymmetric risk. Although the earnings growth of workers in the first quintile of the import penetration have a distribution more asymmetrically positive relative to the ones in the fifth quintile, they already were in the period before the "China-shock". In terms of changes in the asymmetry, regarding the 1-year earnings changes distribution, the Kelley skewness have decreased 38% in the lowest import penetration quintile, whereas it fell by 68% in the highest quintile. Regarding the 5-year earnings changes distribution, the picture is the opposite, the Kelley skewness grew relatively less in the lowest quintile (12%) than in the highest quintile (21%).

Tails

Finally, using both a moment-based and a percentile-based measure, we summarize the behavior of the tails in the regions affected by trade. In particular, we report the fourth central moment and the Crow-Siddiqui kurtosis, defined as:

$$\mathcal{K}_{cs} = \frac{(P97.5 - P2.5)}{(P75 - P25)}. \tag{8}$$

Both the moment-based and the percentile-based measures have higher values for the workers in the highest import penetration quintile, meaning that extreme earnings changes happen more frequently in the regions more affected by trade in both before and after the China shock. Focusing in the changes of these statistics between the two periods gives a noisy picture. In the 1-year income change distribution, in both the percentile and the moment-based measures, the statistics regarding the tail of the distribution increased relatively less in the regions in the 1st import penetration quintile. In the regions less affected by trade, in the case of the fourth central moment, the value decreased 10.41%

[14]E.g. Guvenen et al. (2019) found a coefficient of around -0.2 in the distribution of 5-year earnings growth of prime age workers in the U.S.

[15]See Busch et al. (2018) for the evidence for the U.S., Germany and Sweden.

[16]Average growth in Brazil in the last 30 years has been 2.2%

(from 0.528 to 0.473), when the Crow-Siddiqui kurtosis, increased by 13.3%. In comparison, workers located in the last trade quintile had a decrease of 13.9% in the fourth central moment, and an increase of 12.4% in the Crow-Siddiqui kurtosis. Nevertheless, when we evaluate the 5-year income growth, we observe that workers in the fifth quintile of increased import competition decreased the tail statistics relatively less, from 1.33 to 0.958 (-27%) in the fourth central moment and from 5.58 to 5.89 (5.5%) in Crow-Siddiqui kurtosis, than the regions in the first quintile, which had a decrease of 35.9% and an increase of 15% in the fourth central moments and in Crow-Siddiqui kurtosis respectively.

5 Empirical Strategy

The results of the previous section indicate that there is a correlation between the increase in the imports with China and the changes in dispersion and higher moments in the distribution of income growth in the Brazilian local labor markets. Nonetheless, regions affected by the trade shocks were already substantially different from the other regions before the entry of China in the international markets. In addition, during the same period, the Brazilian labor market experienced an overall decrease in inequality, informality and changes in policy at the national level. Thus, to study the causal effect of trade shocks on earnings' risk, we exploit variation within local labor markets by specifying a regression including both time and regions fixed effects. The model can be interpreted as an extension of the empirical model proposed by Costa et al. (2016), where instead of using the growth of the outcome between 2000 and 2010, we pool all the years between 2000 and 2012 in levels. The proposed regression reads:

$$m_{rt}[\Delta^n y_t^i] = \beta_I IS_{rt-k} + \beta_X XD_{rt-k} + T_{rt}\delta + \alpha_r + \alpha_t + \varepsilon_{rt}, \tag{9}$$

where $m_{rt}[\Delta^n y_t^i]$ represents the moment outcome of microregion r in year t from the distribution $\Delta^n y_t^i$. In our model, m_{rt} are the different measures related to the labor income risk in local markets: the empirical values of dispersion, skewness and kurtosis, as described in the previous section. The terms IS_{rt-k} and XD_{rt-k} are measures of import and export penetration, defined in equations 5 and 6, which can potentially be defined in lags (if $k > 0$). The terms α_r and α_t are microregion and time fixed effects. The term T_{rt} is the vector of time-varying controls at the microregion level. We cluster standard errors at the level of the mesoregion - a set of geographically related microregions - and weight the regressions by the share of national workforce in each local labor market.

The OLS model described in equation 9 suffers from potential endogeneity issues. For example, sectors that experience large changes in the trade pattern with China might also suffer supply or demand shocks due to Brazilian-specific or world-wide factors. In this case, our estimators would be capturing potentially endogenous changes associated with factors correlated to our local labor market outcomes. For example, changes in trade between Brazil and China might reflect sector specific productivity growth in Brazil (e.g. national subsidies to subsector X), changes in internal patterns of consumption due to rising income and inequality reduction or variations in world prices or quantities. Therefore, broadly following the extensive trade literature on the "China Shock" (e.g. Autor et al. (2013)) and, more specifically, Costa et al. (2016), we construct instruments for IS_{rt} and XD_{rt} according to the steps below.

First, we define $\tilde{I}_{ijt}$ and $\tilde{X}_{ijt}$ to be the total imports (exports) of country i in sector j in year t from (to) all countries other than Brazil. Then, we run the following auxiliary regressions, separate by each year t using data on $\tilde{I}_{ijt}$ and $\tilde{X}_{ijt}$ from 2000 to 2012 for all countries available in the COMTRADE trade data except Brazil:

$$\tilde{I}_{ijt} = \alpha_{jt} + \psi_{China,jt} + \nu_{ijt}, \tag{10}$$

$$\tilde{X}_{ijt} = \gamma_{jt} + \delta_{China,jt} + \mu_{ijt}. \tag{11}$$

The left-hand side of the two regressions above is the value of the imports (exports) of a country in a given sector, net of its imports (exports) from Brazil. The sector fixed effect α_{jt} (or γ_{jt}) then captures the mean, across countries, of net-of-Brazil imports (or exports) in that sector; that is, captures world-level shocks such as worldwide prices. The regressions are weighted by 2000 import (export) volumes. This means that the China-specific dummies $\psi_{Chinajt}$ and $\delta_{Chinajt}$ represent the deviation of China's imports and exports in sector j excluding trade with Brazil, as compared to this weighted cross-country average. Finally, the instrumental values are constructed as follows:

$$ivXD_{rt} = \frac{1}{L_{r,2000}} \sum_j \frac{L_{rj,2000}}{L_{Bj,2000}} \hat{\psi}_{Chinajt}, \tag{12}$$

$$ivIS_{rt} = \frac{1}{L_{r,2000}} \sum_j \frac{L_{rj,2000}}{L_{Bj,2000}} \hat{\delta}_{Chinajt}. \tag{13}$$

By running the auxiliary regressions 10 and 11, we estimate the "China shock" in terms of trade world-wide, cleaning the resulting estimates from worldwide trends or from Brazilian specific internal shocks in similar sectors. The fixed effects α_{jt} and γ_{jt} confirm that the pattern of trade of China with the world was provoked by Chinese internal factors and, thus, evolved differently from worldwide trends. This is what enables the identification strategy.

6 Empirical Results

In this section, we summarize the empirical results. Using our baseline specification, we aim to answer two questions: is the evidence on the increase of labor income risk from trade consistent with persistent or transitory idiosyncratic shocks? Does the effect of trade takes time to unfold or it is felt right away? We tackle these by focusing the results on two fronts: (i) comparing the results on the moments from the 5-year and 1-year income growth distributions, (ii) looking at the effect of the contemporaneous trade variables versus its lagged values.

In light of the discussion of Section 2, we emphasize the results on the effect of the contemporaneous values of IS_{rt} and XD_{rt}, as well the two and four year lags, on the moments of the 1-year and 5-year income growth distributions. Higher coefficients of the lags on the distribution of $\Delta^5 y_t^i$, can be interpreted as evidence that part of the effect is accounted by persistent idiosyncratic shocks. To understand this reasoning, we have to think that the distribution of 5-year differences is not only informative about the two years used to compute the individual income, but also about the entire individual history between both points in time. Another interpretation is that the changes on trade simply had a sluggish effect on the labor market. To present evidence of this mechanism, we have to compare the results of different lags and compare it using both the 1-year and 5-year distributions. Since the one year income growth distribution does not have accumulated persistent shocks, the cross comparison help us to differentiate between the two mechanisms.

The coefficients are interpreted as the effect of an increase in a thousand U.S. dollars in trade value per worker on the moments of the income growth distribution. To keep the same sample across all specifications, we restrict it to be the same of the regression on the fourth lag. Finally, we only use moments computed from distributions with at least 50 individuals. These restriction does not affect substantially the results.

6.1 Mean

Although the average income level are not the main focus on the paper, we find useful to start from it before the focus is shifted to the distribution of income change. Table 2 shows the effect of an increase of US$1000 in exports and imports on the log yearly income of a local labor market. The estimated coefficients hint that the regions more affected by the increase in imports suffered a decrease in yearly income. The estimates range from -16% in the contemporaneous specification up to almost -26% in the fourth lag of IS_{rt}. None of the results on the exports are statistically different from zero.

Table 2: Effect of Trade Shocks on the Average Log Income

	Mean		
		y_t^i	
IS_{rt}	-0.162***		
	(0.0242)		
XD_{rt}	-0.000486		
	(0.00198)		
IS_{rt-2}		-0.201***	
		(0.0343)	
XD_{rt-2}		0.00138	
		(0.00213)	
IS_{rt-4}			-0.259***
			(0.0501)
XD_{rt-4}			0.00499
			(0.00562)
N	4537	4537	4537

Notes: The distributions of average log income are constructed using RAIS. The trade data is from CONTRADE. All the regressions include years and microregions fixed effects, and are instrumented by $ivXD_{rt}$ and $ivIS_{rt}$ and their lags when applicable. We include as a control the average age of the workers used to compute the income change distributions. Standard errors in parenthesis are clustered by 130 mesoregions. Regressions are weighted by the share of the national labor force in 2000. *** p<0.01, ** p<0.05, * p<0.1.

We point that Costa et al. (2016) found a positive effect of the impact of Chinese exports on average wage growth, and a relatively less robust negative impact of imports. Given that our results are somewhat different from theirs, we discuss possible reasons here. First, our sample does not cover informal workers and are selected to cover workers highly attached to the formal market. Second, we cover total yearly income, instead of hourly wage level. Providing that a substantial impact of trade comes from changes in hours - for example, through reallocation of labor - the effect on total income can be substantially different from the one on the hourly wage. Specifically, employment reallocation can amplify negative effects and hinder positive wage growth.

6.2 Dispersion

In Table 3, we summarize the impact of the China trade on the dispersion of the income growth distribution. In short, the estimates suggest that an increase in the supply of imports from China is associated with an increase in the dispersion of the distribution. Yet, high values of exports to China does not reduce the dispersion of distribution. The specification shows that the effect of imports, in both the variance and in $P9010$, displays a remarkable pattern: it is higher in the dispersion of 5-year income growth relative to the dispersion of the 1-year income growth distribution and it increases as we use longer lags of the dependent variable. We make sense of this result as evidence that: (i) some of the impact is through persistent idiosyncratic shocks, given the higher coefficient on the distribution of $\Delta^5 y_t^i$ relative to $\Delta^1 y_t^i$ for all lags, (ii) has a sluggish effect, given the higher coefficient of IS_{rt-4} relative to IS_{rt-1}.

With respect to the magnitude of the coefficients, we recall that the values of $P9010$ of the 5-year income changes distribution for the Brazilian microregions range from 0.8 to 1.6 in 2005. The coefficient of IS_{rt-4} implies that an increase of US$1000 per worker in the Chinese imports increase the intercentile dispersion of 90 to 10 by almost 0.1. To put in perspective, if we rank all regions by their respective $P9010(\Delta^5 y_t^i)$, this increase is sufficient to bring a region located in the 25th centile ($P9010 = 1.02$) to the 50th centile ($P9010 = 1.13$). When focusing on the variance the argument withstand, the increase in US$1000 per worker in imports increase the variance in 0.043, and again would imply a jump from the 25th centile (variance of 0.33) to the 50th centile (variance of 0.38).

In the case of exports, the estimates of the impact of XD_{rt} indicate that the increase in the exports to China did not affect the dispersion of income changes. This result is robust to different lags of XD_{rt}, and both measures of dispersion. Although previous evidence points that the regions that were affected "positively" by the China shock had higher wage growth, it is not clear that other moments of the distribution of income growth are changed.

Table 3: Effect of Trade Shocks on the Second Moment of Income Growth

	P9010					
	$\Delta^5 y_t^i$			$\Delta^1 y_t^i$		
IS_{rt}	0.0577***			0.0323***		
	(0.0166)			(0.0110)		
XD_{rt}	0.00368			0.00528		
	(0.00383)			(0.00374)		
IS_{rt-2}		0.0779***			0.0445***	
		(0.0223)			(0.0137)	
XD_{rt-2}		0.00372			0.00816	
		(0.00313)			(0.00539)	
IS_{rt-4}			0.0999***			0.0579***
			(0.0320)			(0.0191)
XD_{rt-4}			0.00348			0.00633
			(0.00608)			(0.00613)
	Variance					
	$\Delta^5 y_t^i$			$\Delta^1 y_t^i$		
IS_{rt}	0.0216**			0.0133**		
	(0.00921)			(0.00546)		
XD_{rt}	0.00217			-0.00156*		
	(0.00175)			(0.000896)		
IS_{rt-2}		0.0303**			0.0184***	
		(0.0119)			(0.00683)	
XD_{rt-2}		0.00147			-0.00167*	
		(0.00117)			(0.000857)	
IS_{rt-4}			0.0434**			0.0262**
			(0.0194)			(0.0107)
XD_{rt-4}			0.000192			0.00188
			(0.00206)			(0.00162)
N	4537	4537	4537	4537	4537	4537

Notes: The distributions of income change are constructed using RAIS. The trade data is from CONTRADE. All the regressions include years and microregions fixed effects, and are instrumented by $ivXD_{rt}$ and $ivIS_{rt}$ and their lags when applicable. We include as a control the average age of the workers used to compute the income change distributions. Standard errors in parenthesis are clustered by 130 mesoregions. Regressions are weighted by the share of the national labor force in 2000. *** p<0.01, ** p<0.05, * p<0.1.

Intuitively, unemployment spells should be lower with the positive demand shock, which in turn should decrease the dispersion of earnings growth. Nevertheless, higher trade induces reallocation of labor and exposure to unexpected changes in the demand from China which can potentially increase income risk. Given that our coefficients are small in magnitude and statistically indistinguishable from zero in most of the specifications, we interpret these results as no connection between the exports and the dispersion of the distribution.

6.3 Asymmetry

As argued before, the dispersion is a good starting point to understand labor income risk, but it may hide important effects if the distribution is not symmetrical. We proceed, then, to analyze the effect of trade on the asymmetry of the distributions. Table 4 outline the results of the baseline regression on the Kelley skewness and on the third central moment. At a first glance, the results on the Kelley skewness point that the increase in imports from China is related to an increase in the mass of negative labor income shocks (a negative coefficient), while the increase of exports seems to be not.

Regarding the third central moment, the impact of trade seems to be much smaller as the coefficients are small and mainly statistically not significant. This noteworthy difference from the Kelley skewness has one easy interpretation. The third central moment is susceptible to extreme observations, while the Kelley measure the asymmetry without considering the first and last deciles. Given the stronger negative results on the Kelley relative to the third central moment, we interpret that increases in the import from China are associated to the increase in the - mildly negative - income changes located in between percentiles 10 and 50, while the relation of negative to positive extreme earning changes are unlikely to be affected by trade.

Another remarkable result is that the effect on the Kelley is larger and significant only for the $\Delta^5 y_t^i$ distribution, while the results on $\Delta^1 y_t^i$, although negative, seem to be much noisier. We interpret this results as evidence that the persistent income shocks have became negatively skewed in regions affected by the increase of imports from China. One question is what the decrease in the skewness of the 5-year income change distribution really means. Note that an employment-to-unemployment-to-employment transition can only generate persistent effects if it is followed by some kind scarring effect, as the strong negative shock is accompanied by a strong positive shock afterwards. Nevertheless, if the job reallocation has an effect on top of the changes in hours (e.g. loss in human capital), it will show up in the distribution of income growth with relatively long years apart.

To understand the magnitude of the coefficients, note that we can re-write equation 7 as $\mathcal{S}_k/2 + 0.5 = (P90 - P50)/(P90 - P10)$. Thus, the coefficient of IS_{rt-4} on $\Delta^5 y_t^i$ suggests that an increase in US\$1000 on imports from China reduces the share of the dispersion $P9010$ accounted by $P9050$ in 2.42 percentage points. In another way, suppose an autarkic region, with a complete symmetrical distribution of income changes ($\mathcal{S}_k = 0$), open to trade and increase its volume of imports from China in US\$1000 ($\mathcal{S}_k = -0.0484$). Then, its ratio of $P9050/P5010$ goes from 50/50 to around 47.5/52.5.

Table 4: Effect of Trade Shocks on the Third Moment of Income Growth

	Kelley Skewness					
	$\Delta^5 y_t^i$			$\Delta^1 y_t^i$		
IS_{rt}	-0.0449***			-0.0143		
	(0.00996)			(0.0111)		
XD_{rt}	-0.00850*			-0.00411		
	(0.00449)			(0.00266)		
IS_{rt-2}		-0.0517***			-0.0188	
		(0.0145)			(0.0166)	
XD_{rt-2}		-0.00874*			-0.00147	
		(0.00499)			(0.00261)	
IS_{rt-4}			-0.0484*			-0.0303*
			(0.0246)			(0.0169)
XD_{rt-4}			-0.0122			0.00431
			(0.00819)			(0.00553)
	Third Central Moment					
	$\Delta^5 y_t^i$			$\Delta^1 y_t^i$		
IS_{rt}	-0.00812			0.00204		
	(0.0207)			(0.00303)		
XD_{rt}	-0.00536**			-0.00242**		
	(0.00262)			(0.00120)		
IS_{rt-2}		-0.0187			-0.00338	
		(0.0291)			(0.00456)	
XD_{rt-2}		-0.00639			-0.00236*	
		(0.00392)			(0.00131)	
IS_{rt-4}			-0.0144			-0.00302
			(0.0410)			(0.00802)
XD_{rt-4}			-0.0131			0.000747
			(0.00909)			(0.00168)
N	4537	4537	4537	4537	4537	4537

Notes: The distributions of income change are constructed using RAIS. The trade data is from CONTRADE. All the regressions include years and microregions fixed effects, and are instrumented by $ivXD_{rt}$ and $ivIS_{rt}$ and their lags when applicable. We include as a control the average age of the workers used to compute the income change distributions. Standard errors in parenthesis are clustered by 130 mesoregions. Regressions are weighted by the share of the national labor force in 2000. *** p<0.01, ** p<0.05, * p<0.1.

6.4 Tails

Finally, Table 5 describes the results on the extreme income changes measure by both the Crow-siddiqui Kurtosis and the fourth central moment. As it was shown in figure 5, the distributions of 1 and 5-year income growth display a large mass of workers with little to none changes in yearly income, while a couple of workers receive large shocks. In a nutshell, an increase in imports from China is associated with the increase in severe income changes only in the 1-year distribution. Moreover, longer lags of IS_{rt} have a higher impact on the tails of the distribution indicating that part of this effect does not unravel right away. In the case of exports to China, the effect is small relative to the imports and it seems to have very little effect on the distributions of income change, if any.

Table 5: Effect of Trade Shocks on the Fourth Moment of Income Growth

	Crow-Siddiqui Kurtosis					
		$\Delta^5 y_t^i$			$\Delta^1 y_t^i$	
IS_{rt}	0.0937			0.919***		
	(0.134)			(0.283)		
XD_{rt}	0.0375			0.0745		
	(0.0266)			(0.0648)		
IS_{rt-2}		0.0135			1.201***	
		(0.157)			(0.403)	
XD_{rt-2}		0.0572			0.163	
		(0.0439)			(0.119)	
IS_{rt-4}			0.0931			1.837***
			(0.244)			(0.627)
XD_{rt-4}			0.0246			0.107
			(0.0347)			(0.0904)
	Fourth Central Moment					
		$\Delta^5 y_t^i$			$\Delta^1 y_t^i$	
IS_{rt}	0.0160			0.0200		
	(0.0312)			(0.0186)		
XD_{rt}	-0.00291			-0.00376		
	(0.00355)			(0.00234)		
IS_{rt-2}		0.0311			0.0402	
		(0.0378)			(0.0264)	
XD_{rt-2}		-0.000426			-0.00178	
		(0.00484)			(0.00258)	
IS_{rt-4}			0.0555			0.0584
			(0.0609)			(0.0373)
XD_{rt-4}			-0.00357			-0.00293
			(0.00620)			(0.00466)
N	4537	4537	4537	4537	4537	4537

Notes: The distributions of income change are constructed using RAIS. The trade data is from CONTRADE. All the regressions include years and microregions fixed effects, and are instrumented by $ivXD_{rt}$ and $ivIS_{rt}$ and their lags when applicable. We include as a control the average age of the workers used to compute the income change distributions. Standard errors in parenthesis are clustered by 130 mesoregions. Regressions are weighted by the share of the national labor force in 2000. *** p<0.01, ** p<0.05, * p<0.1.

The results indicate that an increase in US$1000 per worker in the imports from China increases the Crow-Siddiqui kurtosis of the $\Delta^1 y_t^i$ distribution by 0.919 (in IS_{rt}) to up

1.83 (IS_{rt-4}). The magnitude of the coefficients are also sizable. In 2005, the median microregion in Brazil had a kurtosis of 14.24, and their values range from 12.6 in the 25th centile region to 15.1 in the 75th centile. An increase of 1.83 can make a region with relatively small number of extreme shocks, jump almost two quartiles in terms of kurtosis.

Still, this effect is strong only on the distributions of short horizon income growth, which is argued to have lower welfare effect. A full set of regressions on the distributions of one to five years income growth (including all others in between - not presented) reveals that the impact becomes weaker as the time horizon increases, eventually coming to be statistically indistinguishable from zero at $\Delta^5 y_t^i$. It is important to mention that the coefficients on the fourth central moments follow the same direction as the Crow-Siddiqui kurtosis: higher coefficients (i) of the imports, (ii) lags, on the shorter horizon of income change. However, the point estimates are imprecisely estimated.

7 The Welfare Consequences of the Increase in Risk

In the previous section, we quantify the causal effect of the increase in trade with China in the empirical distributions of income growth. Nevertheless, working with the empirical distribution has one caveat, it does not fully decompose the persistent to the transitory component of the distribution of idiosyncratic shocks. Moreover, our empirical estimates have shown that trade might have larger impact on the persistent component of some moments (dispersion and asymmetry) but also on the on the transitory of others (tails). The literature has shown that persistent idiosyncratic shocks tend to be harder to insure and are associated to larger welfare loss, thus, one question remains: what is the overall welfare effect coming from this increase in risk? Which part is accounted by the changes in the higher moments?

We answer these questions by proceeding as follow. First, we estimate an income process targeting the empirical moments of the distribution of income change before the increasing in trade (e.g. using a national sample of workers from 1996 to 2001). Then, we estimate the same income process but now targeting the same set of moments pre-trade *plus* the counterfactual average increase implied by our causal estimates from the previous season. In particular, we use the (weighted) average increase of IS_{rt} and XD_{rt} from 2000 to 2010 (US\$446 and US\$711 per worker respectively) times the coefficient given by the regressions using IS_{rt-4} and XD_{rt-4}. Finally, we input both income processes in an analytically tractable incomplete markets model to compute the effect of the increase in income risk in consumption and total welfare. We interpret the difference of these measure of welfare as the cost of the increase in labor income risk coming from the China shock.

7.1 The Income Process

In light of the facts established in the previous sections, we perform a full decomposition of the transitory and permanent idiosyncratic risk by estimating a stochastic income process. Although the income process cannot separate the agent's economic choices from unexpected random changes in income, it provides a good fit of the persistent and transitory changes in income. In particular, we estimate a parsimonious version of the process established in Guvenen et al. (2019) that is able to account for the higher moments of the distribution of income growth. Let y_t^i be the log yearly earnings of a worker i at year t. The specified income process is given by:

$$y_t^i = z_t^i + \varepsilon_t^i, \tag{14}$$

$$z_t^i = \rho z_{t-1}^i + \eta_t^i, \tag{15}$$

$$\eta_t^i \sim \begin{cases} N(\mu_{\eta,1}, \sigma^2_{\eta,1}) & \text{with prob. } p_\eta \\ N(\mu_{\eta,2}, \sigma^2_{\eta,2}) & \text{with prob. } 1 - p_\eta \end{cases} \tag{16}$$

$$\varepsilon_t^i \sim \begin{cases} N(\mu_{\varepsilon,1}, \sigma^2_{\varepsilon,1}) & \text{with prob. } p_\varepsilon \\ N(\mu_{\varepsilon,2}, \sigma^2_{\varepsilon,2}) & \text{with prob. } 1 - p_\varepsilon. \end{cases} \tag{17}$$

Where the econometric model includes a persistent component modelled as an AR(1) process with iid innovations η_t^i drawn from a mixture of normal distribution and an iid transitory innovation ε_t^i also drawn from a mixture of normal[17]. The flexibility of the mixture distribution allow us to departure from the log-normal framework and are used to match both the transitory and persistent higher order moments. We restrict the mean of both the persistent and transitory innovations to zero: $E(\eta_t^i) = 0$ and $E(\varepsilon_t^i) = 0$, and set the persistence of the AR(1) to $\rho = 1$[18], effectively making the shock η_t^i fully permanent.

[17] Note the absence of the heterogeneous income profile. The reason is twofold: first, we will only target moments in differences, which does not identify the distribution of fixed effects. Second, as discussed in Guvenen (2009), the heterogeneity of income growth is identified by long lags of the autocovariances of income, in which we have few observations because of the short time period.

[18] We also experimented estimating ρ, finding a value of 0.96. Assuming $\rho = 1$ allows us to derive the analytical results of next section.

We restrict both $\mu_{\eta,1} \geq 0$ and $\mu_{\varepsilon,1} \geq 0$ to guarantee identification.

Finally, we estimate the parameters $\Theta = (\mu_{\eta,1}, \sigma^2_{\eta,1}, \sigma^2_{\eta,2}, p_\eta, \mu_{\varepsilon,1}, \sigma^2_{\varepsilon,1}, \sigma^2_{\varepsilon,2}, p_\varepsilon)$ by minimizing the distance of the simulated moments implied by the income process specified above and their empirical counterparts. Specifically, we target the time-series of the $P9010$, the Kelley skewness and the Crow-Siddiqui kurtosis moments of the earnings growth distribution of $n = 1, 2, 3, 4, 5$. We carry on the Simulated Method of Moments by giving equal weight to all the n-year differences[19]. Intuitively, higher differences ($n \geq 2$) identify permanent shocks, while first differences identify transitory shock. Further details of the estimation method and the intuition for the identification can be found in the Appendix C.2.

Table 6: Estimated Parameters

Scenario	p_η	$\mu_{\eta,1}$	$\mu_{\eta,2}$	$\sigma_{\eta,1}$	$\sigma_{\eta,2}$	p_ε	$\mu_{\varepsilon,1}$	$\mu_{\varepsilon,2}$	$\sigma_{\varepsilon,1}$	$\sigma_{\varepsilon,2}$
Pre "China Shock"	0.3316	0.0135	-0.0067	0.1765	0.1325	0.9519	0.0909	-1.7994	0.1709	0.6275
Post "China Shock"	0.0079	0.9382	-0.0075	0.1589	0.1895	0.0794	0.4423	-0.0381	1.9262	0.0081

Notes: Estimated parameters of the income process under different scenarios. In the Pre-China, we target moments from the 1996-2001 sample. In the post-China, we target moments from the 1996-2001 samples plus the counterfactual increase given by the coefficients of IS_{rt-4} and XD_{rt-4}.

Table 6 presents the estimated parameters using the moments before and after the increase in trade with China. The parameters are similar to the ones found in the literature. The estimated variance of the permanent shock is 0.022 in the period pre-China, and it increases to 0.042 in the post-China.

7.2 The Model

To evaluate how much the idiosyncratic shocks pass through consumption, we use a simplified version of the framework by Heathcote et al. (2014). They adapt an otherwise standard incomplete-markets model to have explicit partial insurance and derive closed form, log linear, solutions of consumption and hours that are functions of the income shocks. The foundation of the model lies in an island structure. Permanent income shocks happen both at the island-level and at the individual level, but agents can only trade risk-free bonds contingents on within-island shocks, leaving no insurance between island-level shocks. Tractability comes from the fact that, in equilibrium, the inter-island wealth

[19]By construction, there are more moments from the 1-year income changes distribution than from the 4-year distribution. We re-weight such that the contribution of all n-year moments to the loss function are the same.

distribution is degenerate at zero, which makes consumption allocations independent from it.

Formally, the model is populated by a continuum of island, which is in turn populated by a continuum of agents. Agents are born without any wealth and survive each period with probability δ. Every period a new generation with mass $(1-\delta)$ enter in the economy. Differently from the original model, we abstract from adjustment in labor supply. Then, the expected lifetime utility of an agent is given by: $W = \mathbb{E}\sum_{t=0}^{\infty}(\beta\delta)^t u(c_t)$.

In the model, log yearly income is the sum of the common average level $\overline{y}$, the island component α_t and the individual component ν_t and evolves as following[20]:

$$y_t = \overline{y} + \alpha_t + \nu_t \tag{18}$$

$$\alpha_t = \alpha_{t-1} + \omega_t \tag{19}$$

$$\nu_t = \kappa_t + \varepsilon_t \tag{20}$$

$$\kappa_t = \kappa_{t-1} + \zeta_t. \tag{21}$$

Where the island-level α_t component follows a random walk with innovations ω_t drawn from distribution F_ω. The individual-level ν_t is given by a fully transitory innovation ε_t drawn from distribution F_ε and a permanent component κ_t with innovations ζ_t drawn from F_ζ.

Given the history of $s^t = (s_0, s_1, ..., s_t)$, where $s_t = (\omega_t, \zeta_t, \epsilon_t)$, assuming log utility and no income taxation, one can shown that consumption is a log-linear function of the uninsurable shock and the average of the within-island insurable component ν_t[21]:

$$\log c_t(s^t) = \overline{y} + \alpha_t + \log\left[\int \exp(\nu_t) dF_\nu\right] \tag{22}$$

To adapt the estimated income process from Section 7.1 into the island framework, we draw from Busch et al. (2018). First, the transitory shock in both processes can be rendered as the same. The permanent shock of 18, however, is the sum of the uninsurable island component, ω, and the insurable individual component, ζ. We assume that both

[20]The average income level $\overline{y}$ will be used to keep the $E(\exp(y))$ to the average income level of 2001.

[21]The assumptions on log utility and no taxation are without loss of generality. One can extend to have CES utility and progressive taxation. Specifically, we decide to not model explicitly progressive taxation since there is no base on how the government is using the taxes to provide public goods, and how much utility the agents are deriving from it.

shocks are drawn from a mixture of normal distribution and re-scale their variance to be a fraction of the total variance of the permanent component η from the estimated process in 7.1. In particular, we assume that the variance of ζ (ω) is scaled to be a fraction ϕ $(1-\phi)$ of η. Thus, we write $\zeta \sim N(\phi^{0.5}\mu_{\eta,i}, \phi\sigma^2_{\eta,i})$ and $\omega \sim N((1-\phi)^{0.5}\mu_{\eta,i}, (1-\phi)\sigma^2_{\eta,i})$ with probability p_η for $i = 1$ and $1 - p_\eta$ for $i = 2$.[22]

7.3 Welfare Results

To compute the expected utility given by the model, we simulate the income history of 10,000 agents using the estimated stochastic process pre-China and its counterfactual post-China. The simulated incomes path are used to compute the consumption history using 22 and total lifetime utility of agent i: $V_i\left(\{c_i\}_{t=0}^{\infty}\right)$. In this experiment, we set $\beta = 0.9615$ and $\delta = 0.996$, and fix the underline moments of the shock distribution's $(F_\omega, F_\zeta, F_\epsilon)$ in all the periods. One key parameter is the degree of partial insurance ϕ. It measures any possible source of informal insurance used to smooth consumption from permanent shocks. Unfortunately, there are no reliable estimates for the Brazilian economy. For the U.S., Heathcote et al. (2014) reports that 45% of the permanent shocks are insurable, while, using a different approach, Blundell et al. (2008) estimates 36%. In these papers, either the tax function is modelled explicitly or net income is used directly. Given that our data is on gross income, we should take into account that transfers may be an additional insurance channel. Nevertheless, it is arguable that partial insurance in a middle income country are somewhat lower than in a developed country. Hence, we will use $\phi = 0.5$ in the baseline, but will report other values for robustness.

We assess the welfare cost of the increase in risk by calculating the consumption equivalent variation (CEV) that makes a unborn agent indifferent between living in the Brazil pre-"China shock" and the - riskier - post China one. Intuitively, this means asking the agent by how much consumption in all future periods and contingencies (in percentage) she is willing to forgone to not be in the riskier labor market. Notice that this value measures only the cost coming from the increase in labor income risk, abstracting from changes in wage levels and other channels. To compare, we also simulate the welfare when only the average income level changes (in the previous simulations we will keep it constant). Using our estimates from Section 6, the average income change is calculated to be -11.20%, which would be exactly the consumption equivalent variation if only the

[22] Note that the mean, variance, skewness and kurtosis of ζ is given by the respective scaled moments of η: $\phi^{0.5}E(\eta)$, $\phi V(\eta)$, $Skew(\eta)$ and $Kurt(\eta)$ (with $(1-\phi)$ for ω)).

mean $\overline{y}$ is changed.

Table 7: Consumption Equivalent Variation

Distribution	$\phi = 0.3$	$\phi = 0.4$	$\phi = 0.5$	$\phi = 0.6$	$\phi = 0.7$
CEV (Higher Moments)	-0.1700	-0.1472	-0.1243	-0.1013	-0.0783
CEV (Log-Normal)	-0.1578	-0.1370	-0.1156	-0.0937	-0.0712

Notes: The table computes the Consumption Equivalent Variation for different values of ϕ: how much consumption in all future periods and contingencies (in percentage) the individual is willing to give up to not go from the pre-China to the post-China stochastic income process. Mixture uses baseline stochastic process, while log-normal assumes the same variance but zero skewness and kurtosis equal to three.

Table 7 shows the results. A newborn agent is willing to give 12.43% of his consumption to stay in the safer labor market. This is the result of the increase in uninsurable consumption inequality coming from the increase in risk. Still, the partial insurance provides a substantial amount of protection in absorbing the increase in risk. We proceed by calculating the contribution of the increase in the non-normal risk. To do so, rather than specify a mixture, we let our income process to be a log-normal (where skewness is zero and kurtosis is 3), but with the same variances as before. It turns out that the contribution of the higher moments is relatively small. The CEV of going from the safer to the riskier labor market, considering only the increasing in dispersion, is 11.56%, roughly 0.9% lower than the full stochastic process. There are two reasons behind this result: (i) the impact of trade in the dispersion is much higher relative to the impact on the asymmetry and tails, (ii) a large part of the observed effect, in the kurtosis, were observed in the 1-year income growth. This translates into the transitory shocks that have less welfare consequences.

Table 8 lays out the sum of discounted utility distribution under different scenarios. After the shocks are realized, because of the increase in dispersion, not everybody loses. Agents in the 90th centile of the are better better off in the post-China world. This does not compensate for the decrease in utility in the other tail, as all agents under the 85th centile are worse off. The same picture occurs if we assume a log-normal stochastic process. In the world pre-China, the utility sum distributions of both mixture and log-normal shocks are remarkable similar to each other. The reason for that is that the stochastic permanent component does not present strong asymmetry or kurtosis. In the post-China world, the higher moments slightly decreases the average utility with respective to the log-normal. A closer inspection in the distribution reveals that this comes from the lower utility from agents below the 75th percentile total utility. Finally, the decrease in the mean income

Table 8: Distribution of Sum of Discounted Utility Realizations under Different Scenarios

	Higher Moments		Log-Normal		Mean-Only	
Percentile	Pre-China	Post-China	Pre-China	Post-China	Pre-China	Post-China
P. 10	203.902	196.495	203.791	196.499	203.902	201.095
P. 25	209.047	203.445	209.032	203.788	209.047	206.241
P. 50	215.118	211.675	215.047	212.152	215.118	212.312
P. 75	220.956	219.965	220.995	220.424	220.956	218.15
P. 90	226.339	227.469	226.276	227.767	226.339	223.533
Variance	75.697	146.025	75.943	146.862	75.697	75.697
Average	215.035	211.898	215.023	212.119	215.035	212.228

Notes: Distribution of the sum if discounted utility simulated under different income processes. Pre and Post-China indicate the parameters of the income processes estimated targeting the set of moments pre and post-China shock. Mixture uses baseline stochastic process, log-normal assumes the same variance but zero skewness and kurtosis equal to three and Mean-only is the same income process of pre-China with higher moments but with a shift in the income level.

shifts down the utility of all agents. Still, all agents below the median would be better in a world where the average income decreases but the risk stays the same.

Finally, the analysis was carried on implicitly assuming that the increase in risk is permanent. We acknowledge that part of the effect might be transitory due to workers and firms reallocation after the trade shock and would fade out once the economy reaches a new steady state. If that is the case, the welfare costs are lower and our results should be interpreted as upper bounds.

8 Conclusion

This paper evaluates empirically the link between trade and labor income risk. The heterogeneity of the Brazilian local labor markets combined with rise of China into being a major player in the international markets provides an ideal natural experiment to understand the effect of the increase in imports and exports on the degree of risk faced by the workers. Specifically, we exploit the increase in the Brazil-China trade flows at the national level, with the industry composition at the local level, to produce import and export measures of exposure to the international markets. Then, using longitudinal administrative data on the Brazilian workers, we construct time and region-specific distributions of n-years income growth and, guided by a region specific income process, interpret it as informative about permanent and transitory idiosyncratic shocks.

We found that an increase in imports from China is associated to an increase in the dispersion of the one and five-year income growth distribution. Moreover, the effect seems to take time to unfold, strengthening the argument that the labor market adjustment to trade shocks is slow. In the case of the asymmetry of the distributions, an increase in imports is linked to an increase in the negative income shocks. The evidence also points toward persistent income shocks, as the effect on the asymmetry is concentrated on the long horizon income growth distribution. On the other hand, regarding the impact on the tails, Chinese imports seems to have stronger impact on the short horizon distributions. Finally, the effects of the increase in exports are small and not significant.

To quantify the welfare consequences of the increase in risk, we estimate a parsimonious stochastic income process using the pre-China distributions of income growth and the counterfactual moments implied by our causal estimates. Afterwards, we input the estimated parameters in an off-the-shelf incomplete markets and compute the welfare cost implied by the increase in labor income risk. We found that a newborn worker is willing to forgo up to 12.43% in consumption to not be part of this riskier labor market.

This paper is a first step to understand the link of China shock and labor income risk. Still, there are several aspects that can be addressed in future research. First, although we present robust evidence on the increase in the persistent idiosyncratic risk, a closer inspection would reveal the source of the risk. Second, there is evidence that trade adjustment can potentially take a long time. Even though we try to address this issue, we can only go so far without losing too much sample. As the outcome of future labor market becomes measurable, future research should be done to understand whether the results hold in even longer time spans. Finally, as the model points out, the welfare consequences on a region that received a large trade shock can potentially be considerable. Given that heterogeneous size of the shocks, the potential for risk sharing among regions is large. One could ask which type of policy could achieve such an outcome.

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Appendix

A Additional Figures and Tables

Table A.1: Second Moment by Sector

	Variance						P9010					
	$\Delta^5 y_t^i$			$\Delta^1 y_t^i$			$\Delta^5 y_t^i$			$\Delta^1 y_t^i$		
						Manufacturing						
IS_{rt}	0.0546***			0.0340***			0.106***			0.0831***		
	(0.00869)			(0.00809)			(0.0237)			(0.0291)		
XD_{rt}	-0.00273			0.000499			-0.00626			-0.00238		
	(0.00257)			(0.00181)			(0.00449)			(0.00397)		
lag2IS_mt		0.0749***			0.0477***			0.142***			0.115***	
		(0.0161)			(0.0116)			(0.0375)			(0.0374)	
lag2XD_mt		-0.000895			0.000110			-0.00380			-0.00462	
		(0.00180)			(0.00194)			(0.00383)			(0.00407)	
lag4IS_mt			0.103***			0.0579***			0.186***			0.133**
			(0.0233)			(0.0159)			(0.0484)			(0.0540)
lag4XD_mt			0.00182			-0.00256			-0.000732			-0.0114
			(0.00455)			(0.00345)			(0.00973)			(0.0135)
N	3647	3647	3647	3647	3647	3647	3647	3647	3647	3647	3647	3647
						Extractive and Agriculture						
IS_{rt}	0.0730**			0.0173			0.159***			0.0571*		
	(0.0337)			(0.0188)			(0.0395)			(0.0328)		
XD_{rt}	0.000927			0.00232			0.00435			0.00413		
	(0.00213)			(0.00266)			(0.00462)			(0.00543)		
lag2IS_mt		0.107**			0.0175			0.216***			0.0587	
		(0.0519)			(0.0243)			(0.0511)			(0.0480)	
lag2XD_mt		-0.00153			0.000570			0.00253			0.00211	
		(0.00290)			(0.00232)			(0.00518)			(0.00483)	
lag4IS_mt			0.124*			0.0289			0.246***			0.117
			(0.0670)			(0.0344)			(0.0713)			(0.0714)
lag4XD_mt			0.000880			-0.00356			0.00507			-0.000347
			(0.00415)			(0.00334)			(0.00805)			(0.00880)
N	3033	3033	3033	3033	3033	3033	3033	3033	3033	3033	3033	3033
						Non-tradable						
IS_{rt}	-0.00894			0.00764			-0.00173			0.0190		
	(0.0119)			(0.00639)			(0.0180)			(0.0136)		
XD_{rt}	-0.00292			-0.00206			-0.00461			-0.00603		
	(0.00276)			(0.00159)			(0.00559)			(0.00483)		
lag2IS_mt		-0.00724			0.0110			0.00579			0.0224	
		(0.0145)			(0.00753)			(0.0223)			(0.0170)	
lag2XD_mt		-0.00211			-0.00218			-0.00315			-0.00851	
		(0.00198)			(0.00150)			(0.00427)			(0.00658)	
lag4IS_mt			-0.00560			0.0182			0.00786			0.0369
			(0.0240)			(0.0125)			(0.0366)			(0.0229)
lag4XD_mt			0.00140			-0.00115			0.00985			-0.00264
			(0.00206)			(0.00132)			(0.00738)			(0.00434)
N	4516	4516	4516	4516	4516	4516	4516	4516	4516	4516	4516	4516

The distributions of income change are constructed using RAIS. The trade data is from CONTRADE. All the regressions include years and microregions fixed effects, and are instrumented by $ivXD_{rt}$ and $ivIS_{rt}$ and their lags when applicable. We include as a control the average age of the workers used to compute the income change distributions. Standard errors in parenthesis are clustered by 130 mesoregions. Regressions are weighted by the share of the national labor force in 2000. *** p<0.01, ** p<0.05, * p<0.1.

B Data

Table A.2: Sectors matched trade-industry data

Sector id	Sector	Sector id	Sector
1103	agriculture - other cereals	19011	manuf - leather processing
1104	agriculture - cotton	19012	manuf - leather products
1105	agriculture - sugar cane	19020	manuf - footwear
1106	agriculture - tobacco	20000	manuf - wood products
1107	agriculture - soya	21001	manuf - pulp and paper
1111	agriculture - flowers and ornamentals	21002	manuf - paper products
1112	agriculture - citrus fruits	22000	manuf - printing and recording
1113	agriculture - coffee	23010	manuf - coke
1114	agriculture - cocoa	23020	manuf - refined petroleum
1115	agriculture - grapes	23030	manuf - nuclear fuel
1117	agriculture - other	24010	manuf - paints and varnishes
1201	agriculture - bovine animals	24020	manuf - pharmaceuticals
1203	agriculture - sheep	24030	manuf - cleaning and hygiene products
1204	agriculture - pigs	24090	manuf - other chemicals
1205	agriculture - birds	25010	manuf - rubber products
1208	agriculture - other animals	25020	manuf - plastic products
2000	forestry	26010	manuf - glass products
5000	fishing and aquaculture	26091	manuf - ceramic products
10000	mining - coal	26092	manuf - other nonmetallic mineral products
11000	mining - oil and gas	27000	manuf - basic metals
12000	mining - radioactive metals	28000	manuf - metal products
13001	mining - precious metals	29001	manuf - machinery
13002	mining - other metals	29002	manuf - domestic appliances
14001	mining - nonmetals for construction	30000	manuf - computing
14002	mining - precious stones	31000	manuf - electrical equipment
14003	mining - other nonmetals	32000	manuf - electronics
15010	manuf - meat and fish	33001	manuf - medical instruments
15021	manuf - fruits and vegetables	33002	manuf - measuring instruments
15022	manuf - oils and fats	33004	manuf - optical equipment
15030	manuf - dairy products	33005	manuf - watches and clocks
15041	manuf - sugar	34001	manuf - motor vehicles
15042	manuf - coffee	34002	manuf - motor vehicle bodies and parts
15043	manuf - other food	35010	manuf - shipbuilding
15050	manuf - beverages	35020	manuf - railway products
16000	manuf - tobacco	35030	manuf - aircraft
17001	manuf - spinning and weaving	35090	manuf - other transport
17002	manuf - other textile products	36010	manuf - furniture
18000	manuf - apparel	36090	manuf - other

C Income Process

In this section, we will describe in details used to derive the results and estimate the income process.

C.1 Central Moments of the Income Process

From the income process of section 2 and assuming $\rho = 1$, we have:

$$\Delta^n y^i_{\mathbf{r},t} = \sum_{k=0}^{n-1} \eta^i_{r_k,t-k} + \varepsilon^i_{r_0,t} - \varepsilon^i_{r_n,t-n}. \tag{A.1}$$

Let us denote $k^j(x(t))$ as the j_{th} cumulant of the of the distribution $F_x(t)$[1]. Then, applying the properties of the cumulants it is easy to see that:

$$k^j(\Delta^n y^i_{\mathbf{r},t}) = \sum_{k=0}^{n-1} k^j(\eta^i_{r_k,t-k}) + k^j(\varepsilon^i_{r_0,t}) + (-1)^j k^j(\varepsilon^i_{r_n,t-n}). \tag{A.2}$$

Where, we can substitute by the central moments $m_x(r,t) = [\sigma^2_x(r,t), \mathcal{S}_x(r,t), \mathcal{K}_x(r,t)]$:

$$\sigma^2(\Delta^n y_{\mathbf{r},t}) = \sum_{k=0}^{n-1} \sigma^2_\eta(r_k, t-k) + \sigma^2_\epsilon(r_0, t) + \sigma^2_\epsilon(r_n, t-n), \tag{A.3}$$

$$\mathcal{S}(\Delta^n y^i_{\mathbf{r},t}) = \sum_{k=0}^{n-1} \mathcal{S}_\eta(r_k, t-k) + \mathcal{S}_\varepsilon(r_0, t) - \mathcal{S}_\varepsilon(r_n, t-n)), \tag{A.4}$$

$$\begin{aligned} \mathcal{K}(\Delta^n y^i_{\mathbf{r},t}) - 3\sigma^4(\Delta^n y^i_{\mathbf{r},t}) = & \sum_{k=0}^{n-1} [\mathcal{K}_\eta(r_k, t-k) - 3\sigma^4_\eta(r_k, t-k)] + \ldots \\ & \ldots + [\mathcal{K}_\varepsilon(r_0, t) - 3\sigma^4_\varepsilon(r_0, t)] + [\mathcal{K}_\varepsilon(r_n, t-n) - 3\sigma^4_\varepsilon(r_n, t-n))]. \end{aligned} \tag{A.5}$$

[1]Cumulants have some useful properties: (i) $k(X+Y) = k(X)+k(Y)$ (for (X,Y) independent), (ii) $k^j(aX) = a^j k^j(X)$ and (iii) $k^j(X+a) = k^j(X)$. Cumulants are closely related to central moments ($\mu^j(X) = E[(X-E(X))^j]$): $k^j(x) = \mu^i(x)$ for $i = 1,2,3$ and $k^4(x) = \mu^4(x) - 3[\mu^2(x)]^2$.

C.2 Estimation

To construct the empirical targets of the estimation, we use a nationwide sample of 100,000 of individuals from 1996 to 2001 applying the same restrictions of the empirical data. Then, we compute the P9010, the Kelley skewness and the Crow-Siddiqui of the $n = 1, 2, 3, 4, 5$ residual earnings growth distribution. We construct two sets of moments: the pre-China, which are just the computed moments of 1996-2001 sample, and the post-China, which are the previous set of moments plus the counterfactual increase given the coefficients of IS_{rt-4} and XD_{rt-4} times their weighted average values. Subsequently, we carry on the estimation of the following stochastic income process:

$$y_t^i = z_t^i + \varepsilon_t^i \tag{A.6}$$

$$z_t^i = \rho z_{t-1}^i + \eta_t^i \tag{A.7}$$

$$\eta_t^i \sim \begin{cases} N(\mu_{\eta,1}, \sigma^2_{\eta,1}) & \text{with prob. } p_\eta \\ N(\mu_{\eta,2}, \sigma^2_{\eta,2}) & \text{with prob. } 1 - p_\eta \end{cases} \tag{A.8}$$

$$\varepsilon_t^i \sim \begin{cases} N(\mu_{\varepsilon,1}, \sigma^2_{\varepsilon,1}) & \text{with prob. } p_\varepsilon \\ N(\mu_{\varepsilon,2}, \sigma^2_{\varepsilon,2}) & \text{with prob. } 1 - p_\varepsilon \end{cases} \tag{A.9}$$

We assume $\rho = 1$ and restrict both $\mu_{\eta,1} \geq 0$ and $\mu_{\varepsilon,1} \geq 0$ to guarantee identification. The goal is to estimate: $\Theta = (\mu_{\eta,1}, \sigma^2_{\eta,1}, \sigma^2_{\eta,2}, p_\eta, \mu_{\varepsilon,1}, \sigma^2_{\varepsilon,1}, \sigma^2_{\varepsilon,2}, p_\varepsilon)$. We proceed by simulating 30,000 of income histories using equation A.1 and compute the counterpart moments of the empirical earnings growth distribution. Let $k_j(\Theta)$ be an arbitrary simulated moment j and their empirical equivalent $\hat{k}_{j,N}$, we define the percentage deviation of the empirical and simulated moment j:

$$F_j(\Theta) = \frac{\hat{k}_j(\Theta) - \hat{k}_{j,N}}{|\hat{k}_{j,N}|}. \tag{A.10}$$

Finally, we stack all moments conditions that have a empirical moments computed using a minimum number of observations ($N >= 150$): $F(\Theta) = [F_1(\Theta), F_2(\Theta), ..., F_J(\Theta)]'$ and minimize the loss function:

$$\hat{\Theta} = \text{argmin}_{\Theta} F(\Theta)' W F(\Theta). \tag{A.11}$$

Where the weighting matrix, W, is chosen such that the contribution of all n-year moments to the loss function are the same. In total, we target 45 moments. Finally, we carry on the minimization problem using a multi-start algorithm similar to Guvenen et al. (2019). In the first stage of the algorithm, we randomly evaluate 5000 initial parameter vectors. Afterwards, based on the loss function, the 5% best guesses are selected and carried for the second stage of algorithm. In that stage, we perform a local search on the selected guesses using the Nelder-Mead simplex algorithm and select the $\hat{\Theta}$ that minimizes equation A.11.

To gather insight on how the moments in differences can identify the idiosyncratic shock, we can adapt the argument of Blundell et al. (2008) using equation A.2. Obviously, since we are not targeting the central moments, the direct identification argument cannot be used. Nevertheless, the percentile-based moments of $P9010$, Kelley skewness and Crow-Siddiqui kurtosis provide similar information, hence, the intuition remains. Suppose that we have four observations such that: $t+1, t, t-1, t-2$. Notice that:

$$k^j(\Delta y^i_{t+1}) + k^j(\Delta y^i_t) - k^j(\Delta^2 y^i_{t+1}) = 2k^j(\varepsilon^i_t) \tag{A.12}$$

$$k^j(\Delta^2 y^i_{t+1}) + k^j(\Delta^2 y^i_t) - k^j(\Delta y^i_{t+1}) - k^j(\Delta y^i_{t-1}) = 2k^j(\eta^i_t). \tag{A.13}$$

Where k^j is the j_{th} cumulant. Intuitively this approach is similar to use the covariances: given that we are using information from $V(\Delta^2 y^i_t) = V(\Delta y^i_t + \Delta^2 y^i_t)$, $V(\Delta y^i_t)$ and $V(\Delta y^i_{t-1})$, we are implicitely using the information from the $cov(\Delta y^i_t, \Delta y^i_{t-1})$. A similar argument can be used for the multivariate moments of the 3rd and 4th central moment (*co-skewness* and *co-kurtosis*). Note that in the case of time-varying distributions, the distributions of the transitory innovation of first period and the last period $(t-2, t+1)$, and the distributions of the persistent innovation of the first, the second and the last $(t-2, t-1, t+1)$ are not identified.