# Trade-induced Local Labor Market Shocks and Asymmetrical Labor Income Risk

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**Abstract**

This paper investigates the relationship between international trade and asymmetrical labor income risk. Using the case study of Brazil, we inspect how an increase in import penetration following the China shock impacted the distribution of idiosyncratic earnings changes across the country's local labor markets, depending on the initial sectoral composition of each region. We find that an increase in import penetration leads to a more disperse and negatively skewed distribution and that these effects can partially be explained by an increase in the volatility of hours worked following job and industry transitions. Moreover, the effect on dispersion grows larger as the lags between periods increase, suggesting a rise in the permanent risk. Through the lens of an incomplete market model, an unborn individual would be willing to forgo up to 4.4% of consumption to avoid the riskier labor market. The welfare cost is half if the higher-order risk is ignored.

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

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# 1 Introduction

A lively and growing body of the economic literature has investigated the properties of individual earnings dynamics across countries, periods, and over the lifetime. Recent contributions have shown that the idiosyncratic income growth distribution has strong nonnormalities and that accounting for the higher-order moments is essential for understanding how this distribution varies over the business cycle (Guvenen et al. (2014), Hoffmann and Malacrino (2019), and Busch et al. (2020)). Despite their unarguable importance, these papers rely mostly on descriptive and correlational evidence and do not aim to provide causal estimates of the impact of economic shocks on idiosyncratic income changes. In contrast, a smaller strand of the literature has tried to understand how trade-induced shocks causally impact earnings risk, finding that a rise in import competition, or a downward tariff change, increases its variance (Krishna and Senses (2014) and Krebs et al. (2010)). Yet, this literature has not explored how such shocks impact the higher-order moments of income growth nor the mechanisms that explain this increased volatility.

This paper aims precisely at filling this gap. In light of the new advances of the income dynamics literature, we first investigate how local labor market shocks induced by trade causally impact individuals' idiosyncratic earnings changes, with a particular focus on the higher-order moments of the distribution. Second, we shed light on some mechanisms behind the observed effects. In particular, we study the differential impact of trade shocks on changes in the distribution of hours worked versus hourly wages, and on the earnings' growth of job and industry switchers in comparison with the stayers. Third, we use our causal estimates to construct a counterfactual permanent-transitory decomposition of the idiosyncratic risk by estimating a stochastic income process that accounts for the higher moments. Finally, we use these estimates to investigate the welfare consequences of the increase in income risk following the trade shock using a partial-equilibrium life-cycle model with incomplete markets.

These are important questions both from the economic literature and from a policy perspective. It is well known that, even keeping average wages constant, riskier labor markets can have pervasive consequences to the individual welfare.[1] Previous evidence has shown that trade shocks might impact the labor market volatility in two ways. First, it can induce reallocation of workers within and across industries, sometimes associated to long unemployment spells and loss of human capital (Dix-Carneiro, 2014). As far as *ex-ante* similar

[1]Individual economic shocks and unexpected income changes often have persistent effects. Jacobson et al. (1993) show that displaced workers have lower wages even 5 years after displacement. In the presence of borrowing constraints, these unexpected and persistent income changes lead to large welfare losses and consumption inequality.

individuals follow different labor market trajectories in response to those events, changes in the trade flows can affect the distribution of earnings growth. Second, trade shocks can have a lasting impact in labor risk if a higher integration with international markets leads to an increase in the specialization of the economy.[2] Importantly, investigating how trade affects the income dynamics of individuals and labor risk, and accounting for the higher moments, is key for a better understanding of its welfare implications and to the design of insurance and labor market policies targeting the most affected workers and regions.

To answer our proposed questions, we use rich administrative data from Brazil, a country that has been widely regarded as an ideal setting to study local labor market shocks induced by trade due to several reasons. First, it experienced a variety of changes in its trade dynamics, from the trade liberalization of the early 90s to the more recent commodities-for-manufactures trade boom with China in the 2000s. 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. Finally, its rich employer-employee matched data covering the *universe* of formal workers allows the construction of individual labor market trajectories and, in particular, of our measures of income growth for each local labor market. Specifically, 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 nonnormal income growth highlighted by Guvenen et al. (2019), our examination is not limited to the variance but also focuses on the asymmetry and tails of the distribution. It is exactly our high-frequency data containing the universe of formal sector workers that allows the examination of *higher-order* moments in *each local labor market*.

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 2015 at the national level, together with local industry composition, to construct a measure of changes in import penetration for each of the 509 Brazilian local labor markets. Our identification approach relies on within local labor market changes in trade exposure, effectively comparing changes in the distribution of idiosyncratic income growth 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

[2] There is an ongoing debate on whether higher integration with international markets increases aggregate volatility. On the one hand, trade allows countries to diversify the sources of demand and supply across countries (Caselli et al., 2020). On the other hand, international trade makes the economy "more granular" and increases the importance of large firms in accounting for fluctuations in output and employment (di Giovanni and Levchenko, 2012). The increase in concentration induced by trade potentially has negative consequences for the labor market. For instance, in a model with firm heterogeneity and labor market frictions, Cosar et al. (2016) shows that higher integration with global markets increases unemployment, wage inequality, and firm-level volatility.

be biased if there are region-varying unobserved factors correlated both with changes in the Brazilian trade with China and with the country's local labor markets structure, such as sector-specific productivity growth or changes in demand 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 an instrument for our measure of changes in import penetration. To the extent that the Chinese trade flows with the rest of the world are unrelated to the Brazilian labor market, this is a valid instrument.

Our empirical results can be summarized as follows. First, we document that the idiosyncratic earnings growth in Brazil, as in other countries, presents strong deviations from the normal distribution, and, importantly, there exists substantial variation of these distributions across the countries' 509 local labor markets. Second, we show that local labor market shocks induced by the rise in import penetration ($\Delta IP_r$) from China increases the dispersion of income growth as measured both by the variance and the P9010. For instance, an increase in a \$1000 per worker in $\Delta IP_r$ increases the variance of five, three, and one-year income growth by 7%, 6%, and 4%, if compared to the national mean values in the baseline year. Importantly, results are systematically larger for longer time-differences, suggesting that import penetration increases not only the transitory but the persistent labor income risk. Moreover, the impact of $\Delta IP_r$ on dispersion is largely concentrated in the lower tail of the distribution. Finally, we turn our focus to the higher-order moments. Results show that an increase in import penetration makes the distribution of income growth more negatively skewed. It also leads to a rise in the share of individuals suffering large negative shocks that is two times the magnitude of the increase in workers receiving large positive shocks. Finally, we found no results of $\Delta IP_r$ on the Crow-Siddiqui kurtosis.

We explore, then, possible mechanisms behind the observed changes. First, we show that the impact of import penetration on the variance of idiosyncratic earnings growth can be largely explained by the increase in the volatility of hours worked annually, with a minor effect on hourly wages. Second, while import penetration increases the dispersion of growth in hours worked in both tails, it increases the dispersion of wage growth in the lower tail only. This could be rationalized by the reallocation of workers in the labor market following the import competition shock, which generally entails a recovery in employment that is not accompanied by a proportionate recovery in wages. This is consistent with the literature that portrays the existence of scaring effects on wages following a job displacement (Jacobson et al. (1993) and Davis and von Wachter (2011)), but little or no scaring effects on hours worked (Ruhm (1991) and Altonji et al. (2013)).

Then, we show that the impact of $\Delta IP_r$ on the variance of idiosyncratic earnings growth is due to effects both in the extensive and the intensive margin of the distribution of job and industry switchers. For instance, an increase of U$1000 in $\Delta IP_r$ increases the fraction of job and industry switchers by 1.4 and 2.6 percentage points when $n = 5$, explaining from one-fourth to one-half of the change in the variance. Moreover, a shock of U$1000 in $\Delta IP_r$ increases the variance of the five-year income growth of job switchers by 0.0533, seven times the effect size on non-switchers. The effect for industry switchers is 0.0444, 9.5 times the size of the estimate for non-switchers. In sum, the individuals that switch jobs or industries often go through unemployment spells and are precisely the ones who experience larger variability in their income. Similarly, the impact of $\Delta IP_r$ on the tails of the income distribution can also be rationalized by an increase in the fraction of switchers who experience large earnings changes.

Afterward, we quantify the welfare cost caused by the increase in labor income risk from the China trade shock. To tackle this question, we estimate two stochastic income processes with higher-order moments: one targeting the empirical distribution of income growth before the increase in trade flows, and another targeting the moments of the counterfactual distribution obtained through our causal analysis. We input the results from the income process into an off-the-shelf incomplete markets model and compute the utility losses, finding that an unborn individual would be willing to forgo up to 4.4% of his consumption to avoid the riskier labor market. Importantly, if we do not account for the nonnormality in the distribution of risk, we would estimate a welfare cost that is half of the size of the one obtained when considering the higher moments.

**Related Literature.** Our paper contributes to different strands of the economic literature. First, it is related to a broad line of work in income dynamics that investigates the volatility of earnings and its implications over time and over the life cycle.[3] Recently, following the work of Guvenen et al. (2019) and Arellano et al. (2017), a growing branch of this literature has started to analyze some deviations of the canonical model of income risk: nonnormality, age-dependence, and nonlinearities. Quantitatively, these new elements have important implications for consumption insurance in the life cycle (Karahan and Ozkan (2013), De Nardi et al. (2020), and Sanchez and Wellschmied (2020)), and over the business cycles (Guvenen et al. (2014), McKay (2017), and Busch et al. (2020)). In particular, these papers documented that the skewness of the earnings growth distribution displays strong procyclical fluctuations for a large set of developed countries.[4] These contributions rely on descriptive

[3]For instance, Storesletten et al. (2004b), Storesletten et al. (2004a), Blundell et al. (2008), Heathcote et al. (2010), Meghir and Pistaferri (2004), and Low et al. (2010).

[4]In the case of Brazil, Gomes et al. (2020) have studied the earnings dynamics out of the formal-informal sector. Because of data limitations, they focus only on one-year earnings growth and do not focus on aggregate fluctuations.

and correlational evidence and mostly focus on the consequences of these fluctuations. We contribute to this literature in three ways. First, to the best of our knowledge, this is the first paper that studies the differences in the earnings growth distribution at local labor markets within a given country, and with a particular focus on the higher moments. Second, we exploit this cross-sectional variation to infer the causal effect of a specific macro shock - a trade shock - on the distribution of earnings growth. Finally, we contribute to the recent discussion of whether the nonnormality of earnings fluctuations are driven by changes in the distribution of wages or hours (Hoffmann and Malacrino (2019), Halvorsen et al. (2020), and De Nardi et al. (2021)). Similarly to Hoffmann and Malacrino (2019), we find that the nonnormality in income fluctuations is mostly explained by the increased volatility of hours worked through employment risk.

Second, we contribute to the literature that investigates the effect of trade openness on the volatility of output.[5] Traditionally, these papers analyze volatility across sectors and individual firms, with only a few studies investigating the effect on the volatility of workers' labor income. The two exceptions are Krebs et al. (2010) and Krishna and Senses (2014). Using Mexican data, Krebs et al. (2010) exploit changes in tariffs to calculate the effect of trade policy on risk, measured at the industry level. The authors find that, in highly protected industries, a change in tariffs is associated with an increase in the variance of the persistent shock, interpreting this result as evidence of the short-run impact of trade openness on income risk. For the U.S., Krishna and Senses (2014) estimate 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. While both papers use relatively short panels (one and three years, respectively) and aggregate workers at the industry level, we rely on richer data that allows for a deeper understanding of the research question. For instance, our paper: (i) exploits variation at the local labor market level instead of national industries; (ii) uses a longer panel that is more informative about persistent innovations; (iii) studies the impact of trade shocks on all workers of the formal sector, not only the ones working on traded-industries and (iv) delves into the study of higher moments, which potentially can have large negative welfare effects.

Finally, we contribute to the vast literature that studies labor market adjustments following trade shocks. 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 papers of Autor et al. (2013) and Autor et al. (2014).[6] In the case of Brazil, the

[5] di Giovanni and Levchenko (2009), di Giovanni and Levchenko (2012), Caselli et al. (2020), and Kramarz et al. (2020).

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

"China shock" had two tales. On the one hand, manufacturing-producer regions suffered from the import competition shock from China. On the other, commodity-exporter regions benefited from the increase in Chinese consumption of such products. 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 for 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), Dix-Carneiro and Kovak (2017) and Dix-Carneiro and Kovak (2019)). Particularly, Dix-Carneiro and Kovak (2019) study the margin of adjustments after the trade liberalization, focusing on workers switching between regions, industries, and formal status. None of these papers have looked at changes in the labor income risk.

The remaining of this paper proceeds as follows. In Section 2, we provide a simple framework that establishes the relationship between income growth and risk. In Section 3, we present the datasets and provide some descriptive statistics, while, in Section 4, we describe our empirical strategy. In Section 5, we present the main empirical results, while, in Section 6, we provide evidence of some mechanisms that explain the patterns observed. Finally, in Section 6, we use coefficients from the causal analysis to estimate the income processes before and after the trade shock and, then, quantify the welfare losses from the increase in risk from trade using a partial-equilibrium incomplete-markets model. In Section 8, we present the conclusion.

# 2 Region-specific Idiosyncratic Risk and Local Labor Market Shocks

To motivate the use of the empirical moments of the distribution of income growth to analyze idiosyncratic risk, we present a simple and flexible stochastic income process. It accounts for time-varying and region-specific distributions of idiosyncratic shocks. Let $y^i_{r,t}$ be the log yearly residual earnings of a worker $i$ at year $t$ in the local labor market $r$:

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

where $F_x(m_x(r,t))$ denotes a parametric distribution $F_x$ with mean 0 and a vector of region and time-specific moments $m_x(r,t)$, characterizing the distribution. The econometric model includes a persistent component, $z^i_{r,t}$, modelled as an AR(1) process with iid innovations $\eta^i_t$ drawn from a distribution $F_\eta$, and an iid transitory innovation $\varepsilon^i_t$, drawn from a distribution $F_\varepsilon$. As usual, the income of a worker $i$ at time $t$ will be represented by the history of accumulated persistent shocks given by $z_{r,t}$ and the transitory shock $\varepsilon_{r,t}$ received in time $t$.

Our final goal is to understand how local labor market shocks (e.g. a trade shock) affect the idiosyncratic income changes (e.g. idiosyncratic risk) of the workers. Our interpretation is that the economic shock impacts the individual labor income risk by changing the underlying distribution from which she draws the innovations $\eta^i_{r,t}$ and $\varepsilon^i_{r,t}$ from. By increasing the dispersion (and possibly higher moments) of $F_\eta$ and $F_\varepsilon$, an increase in import competition makes the labor market of affected regions riskier from the perspective of the individual worker. Hence, the crucial problem rests on extracting the relevant information from the empirical distribution of income changes to infer the changes in the distributions of $F_\varepsilon$ and $F_\eta$.

Given the stochastic process specified in equation (1), one can show that the distribution of income growth of short and long-horizons can be informative of the magnitude of the transitory and persistent shocks. For simplicity, let us set the persistence of the AR(1) to $\rho = 1$, effectively making the shock $\eta^i_t$ fully permanent. Moreover, let us consider only workers who have not moved out of their original labor market.[7] Then, define the income growth from $t-n$ to $t$ of an individual in region $r$ as $\Delta^n y^i_{r,t} = y^i_{r,t} - y^i_{r,t-n}$ and re-write it as:

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

Let the distribution $F_x(m_x(r,t))$ be fully characterized by its variance: $m_x(r,t) = [\sigma^2_x(r,t)]$.[8] We can write the variance of the distribution of $n-$year earnings in year $t$ and labor market

[7] Including movers produce many problems in the identification of region-specific distributions. First, we must keep track of the entire location history of the worker. Otherwise, we might lose track of the original source of the shock. Second, the income growth of movers is inherently different than the one of stayers, and its shocks are likely to depend on both the original and the new region. Finally, 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.

[8] In appendix C.1, we discuss the case where the distribution is characterized by $\mathcal{S}_x$, the third moment, and $\mathcal{K}_x$, the fourth moment.

$r$, $\sigma^2(\Delta^n y_{r,t})$, as a function of the variances of $F_\eta$ and $F_\epsilon$:

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

Equation 3 shows a standard result from the literature of income dynamics: as the difference between the two points in time, $n$, increases, the permanent shocks accumulate and the variance of $\Delta^n y_{r,t}$ grows larger.

Therefore, to identify the impact of the local labor market shock on the distributions $F_\eta$ and $F_\varepsilon$, one should proceed in two steps. The first step is to estimate the impact of the shock on the short and long run empirical moments of the distributions of income growth. The second step would be to contrast the magnitude of the estimated impact of the shock on the short and long-run moments. If the magnitude of the impact is similar in both the long and the short run, the local labor market shock has a stronger impact on the transitory idiosyncratic risk. Otherwise, if the magnitude of the impact is larger in the long run than in the short run, because of the cumulative nature of $\Delta^n y_{r,t}^i$, this is evidence that that the local labor market shock has an impact in the persistent idiosyncratic risk.[9]

# 3 Data and Descriptive Statistics

## 3.1 Individual-level Worker Data

The main data used in the analysis comes from RAIS (*Relação Anual de Informações Sociais*), a Brazilian matched employer-employee panel data from 1995 to 2015. It contains all employment spells of the universe of workers in 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 is a restricted dataset provided by the Ministry of Labor upon approval of research projects. Second, we supplement RAIS with public data from the Brazilian Census of 2000. Since this is not a panel, we cannot use it to construct individual-level income growth. Instead, this data is used to create industry and region-level measures of the labor force for the construction of industry shares and region weights, and additional region-level variables, used as controls.

To compute the workers' yearly labor income, we aggregate all the individual employment

[9]We acknowledge that income growth is not only driven by unexpected changes but also by individual choices. Unfortunately, separating decisions from unexpected income changes requires either additional data or structure (e.g. an economic model). Therefore, for the remainder of the paper, we follow the majority of the income dynamics literature and use the distribution of earnings change as analogous to labor income risk.

spells in RAIS in a given year. Then, we assign the worker a 5-digit industry code and a municipality based on the longest employment spell of that year. Our sample restriction is standard in the literature. To alleviate concerns that individuals may take human capital and retirement decisions, we select workers between 25 and 55 years old that had positive earnings in the given year. Furthermore, motivated by the discussion in section 2, we select workers who did not move out from their original local labor market.

Our largest concern about the data is that it only covers formal employers, making an unemployment spell indistinguishable from employment in the informal sector. Brazil has a large informal sector and previous evidence has shown that trade shocks might affect the degree of the informality of local markets.[10] This could potentially bias our estimates. To overcome this issue, we restrict our sample to individuals highly attached to the formal labor market and maintain in our baseline sample only workers employed in the formal sector for a minimum number of years between 1995 and 2015. 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 the less prone to be impacted by changes in informality. Furthermore, this sample stability is important in the comparison of short and long-run income changes. Nevertheless, imposing a restriction of too many years of employment may result in the loss of important unemployment dynamics, underestimating the observed income risk. In the end, we found seven years a good balance between this trade-off.[11]

Our unit of analysis is the region 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 them as regions or local labor markets interchangeably to avoid repetition. Finally, except in the largest regions where we randomly select 750 thousand individuals, we use all observations that satisfy our restrictions. Our final sample adds up to around 339.8 million worker-year observations, roughly 30.4 million individuals distributed over 21 years in 509 local labor markets.

Table 1 provides a comparison between a nationally representative sample from RAIS with the restrictions discussed above (column 1), a sample from RAIS with only the age restrictions (column 2), and different subsamples from the Census (columns 3, 4 and 5). First, it is reassuring that the sample from RAIS with only age restrictions (Column 2) is similar to the sample of formal workers from the Census (column 3). While the average

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

[11] The individual has to be observed for at least seven years (not necessarily consecutive) in the same region. Results are robust for other period thresholds. Yet, note that it is necessary to restrict the sample for a minimum threshold of around five years. If, for example, we keep in the sample individuals observed in the formal labor market for only two years, we would end up with a large sample of workers not highly attached to formal vacancies. Then, we would have a much larger sample for the analysis of short-run income changes than the one for studying long-run income changes, which could confound our results.

Table 1: Summary statistics from RAIS and Census in year 2000

| | RAIS | | Census 2000 | | |
|---|---|---|---|---|---|
| | Baseline (1) | All RAIS (2) | Formal (3) | Formal & Informal (4) | All (5) |
| Annual labor income | 9018.42 | 8537.08 | 9507.53 | 7903.12 | 9075.92 |
| Monthly labor income | 829.71 | 793.68 | 792.29 | 658.59 | 756.33 |
| Hours worked per week | 41.1 | 40.8 | 43.8 | 43.8 | 44.5 |
| Months worked per year | 10.3 | 10.0 | - | - | - |
| Average age | 36.4 | 36.8 | 36.7 | 36.7 | 37.5 |
| Share Male | 64.0 | 58.6 | 58.7 | 57.4 | 61.9 |
| Education Level | | | | | |
| Less than high school | 30.6 | 33.2 | 56.9 | 64.5 | 66.7 |
| High school | 43.5 | 40.5 | 30.0 | 25.1 | 23.4 |
| College | 25.9 | 26.3 | 13.1 | 10.3 | 9.9 |
| Sector | | | | | |
| Share agriculture | 4.2 | 4.3 | 5.7 | 9.4 | 12.6 |
| Share manufacturing | 19.5 | 17.3 | 17.7 | 15.3 | 13.8 |
| Non-tradable | 76.3 | 78.4 | 76.6 | 75.3 | 73.5 |
| Years in RAIS during 1995-2017 | 15.5 | 11.2 | - | - | - |
| Share formal workers | 100.0 | 100.0 | 100.0 | 69.6 | 48.2 |

*Notes*: All columns include workers between 25-55 years old with positive labor income in 2000. *Baseline* is a national random sample of 400,000 workers used in the main analysis: non-movers highly attached to the formal labor market. *All RAIS* is the national random sample of 200,000 workers with only the age restriction. *Formal* includes paid workers in the Census formally employed. *Formal & Informal* adds informal paid workers. *All* includes additionally self-employed and entrepreneurs. Values in 2000 Brazilian Reals.

monthly income in 2000 in RAIS is given by 793 BRL, this value is 792 in the Census.[12] Furthermore, the demographics match quite closely. The share of men and the average age are, respectively, equal to 58% and 36 years old in both RAIS and the Census. One potential concern is the differences across educational levels. For instance, the sample from RAIS has an average of 26.3% of college-educated individuals, roughly double of what is observed in the Census. We attribute these differences to how education is collected in the two data sets. In the Census, the number of years of education is reported directly by the worker, white in RAIS, the education category is filled by the employer. Unlike income, which is collected for tax purposes, education is filled to construct a worker record and there is no formal punishment if the employer misreport. Hence, it is likely that many firms do no track the precise level of education of their employees and report an approximation.

[12] Notice that the annual labor income differs substantially between RAIS and the Census. This is the case because, while in the Census annual income is the monthly income times twelve, in RAIS, the annual income is the individual monthly income multiplied by her employment spell.

Regarding the sample of workers highly attached to the formal labor market (Column 1), the average individual earns a higher income, is slightly better educated, has a higher likelihood to be male, and works 0.3 more months per year. This is unsurprising since high-income workers tend to transit less to the informal sector (Gomes et al., 2020). Hence, they are over-represented in our baseline sample. One important characteristic of our baseline sample is its initial sectoral share. The agricultural/extractive sector is particularly under-represented at RAIS. Only 4.2% of the workers are located in industries from the agricultural/extractive sector, while in the full Census (Column 5), around 12.6% of the total labor is employed in these industries. On the other hand, the sample from RAIS over-represents the manufacturing industries in 2000. Roughly 19.5% of the sample comprises workers in the manufacturing industries, almost 6 p.p more than in the full sample from the Census.

## 3.2 Distributions of Labor Income Growth

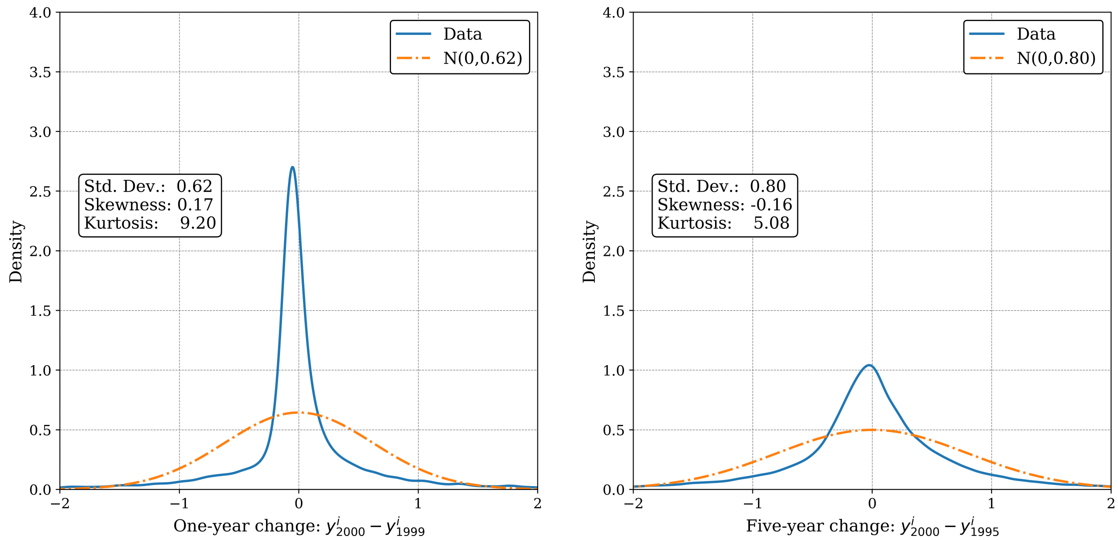
The empirical objects of our analysis are the distributions of differences of annual log labor income net of age and year effects. To construct these distributions, we compute the residuals of a regression of log income on age and year dummies for each local labor market.[13] Precisely, we define the moment of a distribution in local labor market $r$ for period $t$ as $m[\Delta^n y^i_{r,t}]$, where $\Delta^n y^i_{rt} \equiv y^i_{r,t} - y^i_{r,t-n}$ is the residual-earnings growth of individual $i$ between $t$ and $t-n$.

Our analysis has 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 from one year to the other. In Figure 1, we plot the distributions of one ($\Delta^1 y^i_{2000}$) and five-year ($\Delta^5 y^i_{2000}$) earnings growth in Brazil, confirming that the asymmetrical leptokurtic distribution is also present in our context. Here, we compute $m[\Delta^n y^i_t]$ with a national sample of 400,000 workers, instead of estimations for each local labor market. As illustrated in the figure, even distributions with the same standard deviation could have different income dynamics. Thus, assuming normality would entail a great loss of information. Therefore, to paint a complete picture of the labor income risk, we also rely on statistics that help the evaluation of the asymmetry and the tails of the distribution.

Table 2 presents selected moments of the distributions of one ($m[\Delta^1 y^i_{2000}]$) and five-year ($m[\Delta^5 y^i_{2000}]$) earnings growth in Brazil (Column *Nat.*) and in the local labor markets

[13]Our goal is to characterize the differences of the residuals as unexpected idiosyncratic income shocks. The year dummies clean region shocks common across workers, while the age dummies proxy for expected income growth from experience and tenure. An alternative specification is to include additional factors accounting for occupations, industries, or employers. We do not include these factors because our aim is to capture the income changes produced by changes in the occupation/employer.

Figure 1: Distribution of Log Earnings Changes: One and Five-year changes




*Notes:* The distribution is computed using 400,000 individuals from a national sample. The growth rate is taken between the years of 2000-1999 and 2000-1995. The density is computed using a Gaussian Kernel with bandwidth equal to 0.05.

($m[\Delta^1 y^i_{r,2000}]$ and $m[\Delta^5 y^i_{r,2000}]$).[14] Columns P25, P50, and P75 refer to regions in the $25^{th}$, $50^{th}$ and $75^{th}$ percentiles of the distribution of the respective moment among the Brazilian local labor markets. They show that, in the initial period of our sample, the distributions of earnings growth already display substantial variability across regions. This could reflect persistent differences regarding the dynamism of the labor market that arise from institutional factors, as well as temporary economic shocks that had a heterogeneous impact on these regions.

We report two standard measures of dispersion: the variance and the $P9010$. The $P9010$ is defined as the difference between the $90^{th}$ and $10^{th}$ percentiles of the income-changes distribution and is robust to extreme observations. Both measures show that there is substantial dispersion in the distribution of earnings growth and that dispersion is larger for the $5^{th}$ lag of income differences. Furthermore, regions in $75^{th}$ percentile are roughly 21% more disperse than the regions in the $25^{th}$ percentile for $Var[\Delta^1 y^i_{r,2000}]$ and 23% for $Var[\Delta^5 y^i_{r,2000}]$.

To measure the asymmetry, we rely on two measures. First, we use a quantile-based measure of skewness, the Kelley skewness:

$$\mathcal{S}_k = \frac{(P90 - P50) - (P50 - P10)}{(P90 - P10)}. \tag{4}$$

[14] Table A.1 presents the same moments for the distribution of three-year earnings growth ($m[\Delta^1 y^i_{2000}]$).

Table 2: Moments of One and Five-year Income Changes

| | $m[\Delta^1 y^i_{2000}]$ | $m[\Delta^1 y^i_{r,2000}]$ | | | $m[\Delta^5 y^i_{2000}]$ | $m[\Delta^5 y^i_{r,2000}]$ | | |
|---|---|---|---|---|---|---|---|---|
| | Nat. | P25 | P50 | P75 | Nat. | P25 | P50 | P75 |
| *Dispersion* | | | | | | | | |
| Variance | 0.383 | 0.342 | 0.371 | 0.412 | 0.639 | 0.564 | 0.658 | 0.692 |
| P9010 | 1.011 | 0.880 | 0.992 | 1.113 | 1.627 | 1.519 | 1.643 | 1.724 |
| P9050 | 0.575 | 0.514 | 0.553 | 0.638 | 0.834 | 0.781 | 0.834 | 0.900 |
| P5010 | 0.436 | 0.344 | 0.428 | 0.488 | 0.793 | 0.695 | 0.817 | 0.862 |
| *Asymmetry and Tails* | | | | | | | | |
| Skewness (Kelley) | 0.138 | 0.107 | 0.160 | 0.211 | 0.026 | -0.038 | 0.023 | 0.101 |
| $P(\Delta^n y^i_t > 0.5)$ | 0.116 | 0.103 | 0.109 | 0.128 | 0.199 | 0.183 | 0.198 | 0.221 |
| $P(\Delta^n y^i_t < -0.5)$ | 0.089 | 0.078 | 0.088 | 0.098 | 0.147 | 0.126 | 0.149 | 0.163 |
| Kurtosis (C.S.) | 12.718 | 11.736 | 12.915 | 13.524 | 5.789 | 5.398 | 5.877 | 6.109 |

*Notes:* Values of $m_{r,2000}[\Delta^1 y^i]$ and $m_{r,2000}[\Delta^5 y^i]$. The skewness stands for the Kelley skewness, the kurtosis stands for the Crow-Siddiqui kurtosis and $P9010 = P90[\Delta^n y^i] - P10[\Delta^n y^i]$. The column Nat. presents the moments for a national random sample of 400,000 workers. Columns P25, P50 and P75 denote the first, second, and third quartile moment value of 509 Brazilian local labor labor markets. Only moments calculated with more than 100 workers are used. Quartiles are weighted by the local labor labor workforce.

This measure has been widely used in the literature for two reasons: (i) it is robust to outliers, as it does not use observations in the top and bottom deciles, and (ii) it provides an intuitive way to decompose overall dispersion in the fraction that is accounted for by the upper tail ($P90-P50$) and the one accounted by the lower tail ($P50-P10$). Notice that the Kelley Skewness is bounded by $(-1, 1)$. Then, a positive skewness means that the dispersion of the upper tail is larger than the dispersion of the lower tail. Furthermore, we can rewrite the skewness as $\mathcal{S}_k/2+0.5 = (P90-P50)/(P90-P10)$. This simple formula gives the share of dispersion that is accounted by the upper tail of the distribution. Table 2 shows that the upper tail explains 57% of the dispersion of $\Delta^1 y^i_{2000}$ and 51% of $\Delta^5 y^i_{2000}$. Again, there is substantial variation in the asymmetry across regions. The *Skewness*$[\Delta^1 y^i_{2000}]$ is roughly two times larger in regions in the $75^{th}$ percentile than in the ones in the $25^{th}$ percentile. Moreover, the *Skewness*$[\Delta^5 y^i_{2000}]$ is even more heterogeneous, with P25 acquiring a negative value.

Finally, to examine the tails of the distribution, we use three main statistics. First, we rely on the Crow-Siddiqui Kurtosis, a percentile-based measure of kurtosis, formally defined as: $\mathcal{K}_{cs} = (P97.5 - P2.5)/(P75 - P25)$. A high kurtosis implies a leptokurtic distribution, where most of the workers undergo very small income changes, while few workers suffer very large shocks. Corroborating what is shown in figure 1, the kurtosis is substantially higher for $\Delta^1 y^i_{2000}$ than for $\Delta^5 y^i_{2000}$. This is expected. As the differences between time periods increase, more individuals endure income shocks and the distribution of income growth approximates a normal distribution. The kurtosis, however, pools both tails together. A simple way to inspect each tail independently is to look at the share of large positive and negative changes. As also expected, Table 2 shows that the share of income growth higher than 50%, $P(\Delta^n y_t^i > 0.5)$, and the share of income growth lower than -50%, $P(\Delta^n y_t^i < -0.5)$, are larger for $\Delta^5 y_{2000}^i$ than for $\Delta^1 y_{2000}^i$. Moreover, a comparison between these moments confirms that the share of positive shocks is larger than the share of negative ones, corroborating the finding for the skewness.

### 3.3 Brazil - China Trade

The data on international trade comes from BACI, a harmonized publicly available version of the United Nations COMTRADE database constructed by CEPII (Gaulier and Zignago, 2010). We gather annual data of imports and exports from 1996 to 2015, of each country with the rest of the world (aggregate) and with Brazil, at the 6-digit Harmonized System level (HS6). The empirical strategy requires the matching between the finer commodity-level trade data with the more aggregated sector-level (CNAE 1.0[15]) data available at RAIS. We create a mapping between the two that results into 76 traded sectors, including 18 agricultural, 8 extractive and 50 manufacturing sectors (Tables A.2 and A.3, in the appendix).

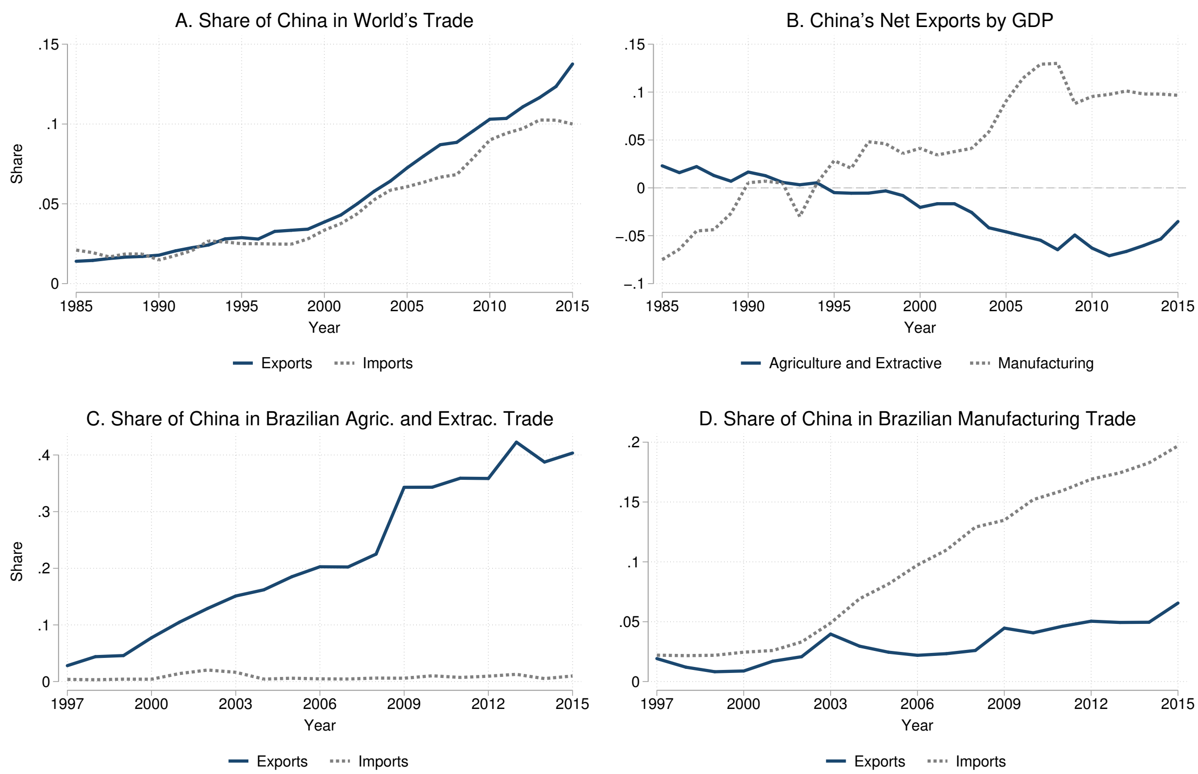
Since the trade behavior of countries and companies are intertwined and jointly determined by the decisions' of their trade partners, identifying the impact of trade shocks on local labor markets poses substantial empirical challenges. In this context, the rapid rise of China into the leading trade nation and the second-largest economy in the world offered an opportunity to circumvent the identification concerns of applied economists.[16]

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. Despite the implementation of numerous reforms with the end of the Maoist era in 1976, the Chinese trade expansion did not begin until the early 1990s, as seen in Figure 2 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 Chinese isolation during the decades of the Maoist period created an enormous opportunity for a future catch up. Between 1952 and 1978, China's GDP Per Capita went from the $59^{th}$ position in the world

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

[16]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 2: The rise of China in International Trade




*Notes:* Panel A plots the share of Chinese participation in the world's merchandise trade, while Panel B plots Chinese net exports (total exports minus total imports) divided by its GDP. Panel C plots the Chinese participation in Brazilian agricultural and extractive trade, while Panel D plots the Chinese participation in Brazilian manufacturing trade. The data source for Panels A and B is the WTO database (http://data.wto.org/), while for Panels C and D is the BACI.

to the $134^{th}$.[17] Thus, China's astounding growth from the beginning of the 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 differently affected countries and local labor markets, according to their previous sectoral specialization. Figure 2 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 as a 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

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

cities, following the decollectivization of Chinese agriculture, 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 2, Panel A). In 2001, China joined the World Trade Organization (WTO), implementing a series of changes in favor of trade liberalization. These included the 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 trade, while the importance of China as a trade partner for Brazil increased significantly. For instance, 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. The increase in Chinese participation in international trade, combined with its comparative advantages, culminated in 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 2 Panels C and D, we plot the share of Chinese participation in the Brazilian exports and imports by sector. The Chinese share in Brazilian exports went from 3.9% to 34.7%, from 1997 to 2015, in the agriculture and extractive sectors, 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.

Although the *China rise* also provoked positive export demand shocks in the agriculture and extractive sectors in Brazil and other commodity-based economies, the negative import competition shocks in the manufacturing sector are of special relevancy for this study. This is so for two reasons. First, a large body of the literature has documented that idiosyncratic earnings risk is highly persistent and countercyclical.[18] Intuitively, unemployment risk associated with large earnings losses should rise in the presence of negative shocks. Therefore, it is expected that an import-competition shock would have an effect on the distribution of earnings growth. It is unclear, however, whether positive shocks would decrease idiosyncratic risk. On the one hand, the likelihood of large unemployment spells would likely decrease. On the other hand, a positive trade shock might induce reallocation of factors, which could increase idiosyncratic income changes in the short run. The overall effect is *ex-ante* unclear. Additionally, positive demand shocks induced by the China rise affected the agricultural and extractive sectors the most. As seen in Table 1, most workers of these sectors are, however, employed in the informal economy, and, thus, not present in our employer-employee matched data. Therefore, even if positive demand shocks positively affect some dimension of income risk, this effect would likely not be fully captured in our analysis due to our data limitation.

[18] See Storesletten et al. (2004a) and Hoffmann and Malacrino (2019).

Indeed, this is actually what we observe empirically. In Appendix B, we show the complete set of results on the effect of export penetration on different moments of the distribution of earnings growth, finding little expressive results. Hence, for the remainder of this paper, we focus on the impact of negative import-competition shocks in the formal sector.[19]

In order to study how imports affect the local labor markets, we define the following measure for import penetration:

$$\Delta IP_{r\tau} = \frac{1}{L_{r,2000}} \sum_{j} \frac{L_{rj,2000}}{L_{Bj,2000}} \Delta V_{CjB,\tau} \tag{5}$$

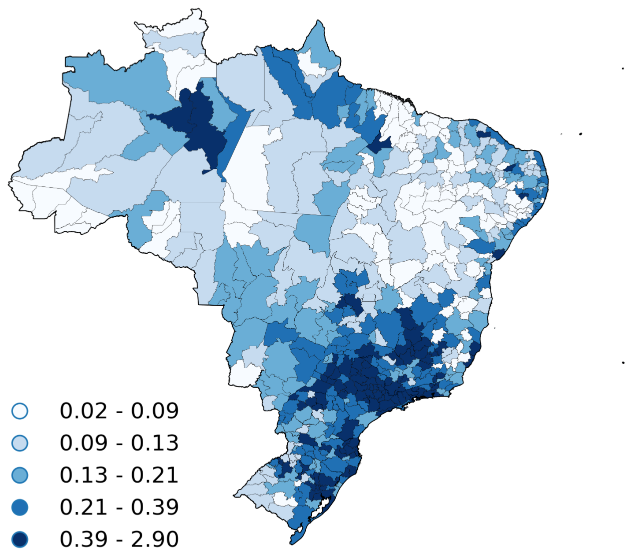
where $j$ represents the sector and $r$ the region. The term $\Delta V_{CjB,\tau}$ denotes the change in the value of Brazil's imports from China from year $\tau$ and year 2000 ($\Delta V_{CjB,\tau} = V_{CjB,\tau} - V_{CjB,2000}$). In our baseline specification, we use the year 2015 as the final year of the China shock, and therefore, we abstract from the subscript $\tau$ from now on.[20] The variable $L_{rj,2000}$ is defined as the size of the workforce in sector $j$ in region $r$, while $L_{Bj,2000}$ and $L_{r,2000}$ are the Brazil's wide work-force in sector $j$ and the total workforce in region $r$, all measured in 2000. The construction of these variables follows the broad literature of Bartik-type instruments, which uses interactions of initial local shares with national growth rates. Variable $\Delta IP_r$ is measured in thousands of dollars per worker.

Figure 3 plots the distribution of $\Delta IP_r$ across the 509 Brazilian regions. As measured by $IP_r$, the average Brazilian region received an import penetration shock from China of US\$467 per worker. The distribution of shocks is highly dispersed and skewed to the right. The regions in the $25^{th}$, $50^{th}$ and $75^{th}$ percentiles received a shock of US\$169, US\$346 and US\$664 per worker, respectively. Finally, as expected, we can see from Figure 3 that the largest import-penetration shocks occur in the most industrialized areas of the country: the South, the South-east and the free economic zone of the city of Manaus, in the North. In this line, Costa et al. (2016) show that the regions most exposed to Chinese imports tended to have a lower proportion of workers engaged in agriculture, a higher proportion working in manufacturing, a smaller share of rural residents, and a greater share of the workforce in formal jobs than the mean Brazilian region in 2000.

[19] This is different from the work of Costa et al. (2016). They use the Brazilian Census, which also includes workers in the informal sector, finding positive effects of demand shocks in the agricultural and extractive sectors on wage growth. In our case, however, since the Census is not a panel data, we cannot use it for the estimation of income risk.

[20] We set $\tau$ equal to 2015 to capture the impact of the full development of the China shock. As seen in Figure A.1, $\Delta IP_{r\tau}$ increases sharply between 2000 and 2011 and only becomes relatively stable in period 2011 to 2015. In Table A.4, in the Appendix, we run some robustness tests with other values for $\tau$ and results remain virtually the same.

Figure 3: Distribution of changes in Import Penetration ($\Delta IP_r$)




*Notes:* The figure plots the distribution of variable $\Delta IP_r$ across Brazilian local labor markets. $\Delta IP_r$ measures changes in import penetration from 2000 to 2015, as defined by equation 8. Values are measured in thousands of dollars per worker and plotted by quintiles.

# 4 Empirical Strategy

To study the causal effect of trade shocks on earnings' risk, we estimate the following model:

$$m[\Delta^n y^i_{r,t}] = \beta_1 \Delta IP_r + \beta_2 m[\Delta^1 y^i_{r,2000}] + W'_{r,2000}\delta + \alpha_a + \varepsilon_r, \tag{6}$$

where $m[\Delta^n y^i_{r,t}]$ defines moments from the distribution of income changes $\Delta^n y^i_{r,t} \equiv y^i_{r,t} - y^i_{r,t-n}$ of region $r$. Specifically, $m_{r,t}$ are the different moments used to evaluate the dispersion, asymmetry, and tails of the distribution of earnings growth in the local labor markets, as described in the previous section. The subscript $n$ defines the difference between the periods from which the distribution of income changes is computed, and the subscript $t$, the final year. In our baseline specification, we present results in which we set $t$ equal to 2015 and $n$ equal to 1, 3, and 5.[21]

The term $\Delta IP_r$ defines the import penetration growth between years 2000 and 2015, as described in equation 5. In practice, following Autor et al. (2013), $\Delta IP_r$ is the change in Chinese import exposure per worker in a region, where imports are weighted according to the

[21] Again, we define $t$ equal to 2015 to capture the impact of the full development of the China shock on the distribution of earnings' risk. In our baseline specification, we set n equal to 1, 3, and 5 to provide results in line with the literature of earnings' risk. Yet, we provide some results for n as large as 15.

local labor markets' share in the national-industry employment. The variable $m[\Delta^1 y^i_{r,2000}]$ is the moment of region $r$ computed from the distribution of income changes between 1999 and 2000. It accounts for regional differences observed in the outcomes for pre-periods, analogously to control for pre-trends.[22]

Additionally, the term $W'_{r,2000}$ is the vector of region-level controls defined at the year 2000. It includes the mean age of workers employed in the formal sector, the share of workers with high school and less of high school education, the size of the local workforce, the share of workers employed in informal jobs, the proportion of rural residents, and a cubic polynomial of income per capita. We also control for the share of each region's workforce employed in agricultural, extractive, and manufacturing sectors in 2000. Importantly, by including controls for the baseline economic structure of each local labor market, we are comparing regions with the same sectoral composition based on the three broad sectors (manufacturing, agriculture, and extractive), but that differ in product or industry specialization *within* these broadly defined sectors.[23] It is precisely this heterogeneity that allows the cross-sectional variation in trade exposure necessary for the identification.

Additionally, in our preferred specification, we include fixed effects $\alpha_a$ for the five main geographic areas in Brazil as defined by the Brazilian Institute of Geography and Statistics (IBGE): North, Northeast, Center-east, South, and South-east. Each of these areas includes neighbor states that share similarities in terms of economic, social, and geographic characteristics. As observed in Figure 1, the largest import penetration shocks are concentrated in the South and the South-east areas, the most industrialized zones of Brazil. Therefore, the inclusion of geographic areas fixed effects performs a comparison of regions *within* each of these areas. Finally, we cluster standard errors at the mesoregion level and weight the regressions by the share of the national workforce in each local labor market.

Despite the extensive inclusion of local-level controls, as described previously, the OLS model of equation (6) might still suffer from potential endogeneity issues. For example, regions affected by the trade shocks could be different from the other ones before the entry of China into the international markets in some unobserved dimensions that we cannot control for. Also, sectors that experience large changes in the trade pattern with China might suffer supply or demand shocks due to Brazilian-specific or worldwide factors. In this case, our estimators would be capturing potentially endogenous changes associated with

[22]In Table A.5, in the Appendix, we also include $m[\Delta^5 y^i_{2000}]$, controlling for a longer-period pre-trend and find virtually the same results.

[23]As explained in Costa et al. (2016), this strategy is feasible because the distribution of Brazil–China trade growth is skewed across sectors. Approximately 40% of the total growth in Brazil's imports from China between 2000 and 2010 is accounted for by electronics (19%), machinery (13%), and electrical equipment (8%).

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 certain subsector), 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 $\Delta IP_r$ according to the steps below.

First, we define $\tilde{X}_{ijt}$ to be the total exports of country $i$ in sector $j$ in year $t$ to all countries other than Brazil. Then, we run the following auxiliary regressions, using data on $\tilde{X}_{ijt}$ in 2000 and 2015 for all countries available in the CEPII trade data except Brazil and setting $\Delta\tilde{X}_{ij} = \tilde{X}_{ij,2015} - \tilde{X}_{ij,2000}$:

$$\frac{\Delta\tilde{X}_{ij}}{\tilde{X}_{ij,2000}} = \gamma_j + \delta_{Chinaj} + \mu_{ij} \tag{7}$$

The left-hand side of the regression above is the growth rate of the exports of a country in a given sector, net of its exports to Brazil. The sector fixed effect $\gamma_j$ then captures the mean growth rate, across countries, of net-of-Brazil exports in that sector; that is, captures world-level shocks such as worldwide price changes. The regressions are weighted by 2000 export volumes. This means that the China-specific dummy $\delta_{Chinaj}$ represents the deviation in growth rates of China's exports in sector j, excluding trade with Brazil, as compared to this weighted cross-country average. Then, we define $\Delta\hat{I}_j = I_{j,2000}\hat{\delta}_{Chinaj}$. The instrumental variable is then constructed as follows:

$$iv\Delta IP_r = \frac{1}{L_{r,2000}} \sum_j \frac{L_{rj,2000}}{L_{Bj,2000}} \Delta\hat{I}_j \tag{8}$$

By running the auxiliary regressions 7, we estimate the "China shock" in terms of trade globally, cleaning the resulting estimates from worldwide trends or from Brazilian specific internal shocks in similar sectors. The fixed effects $\delta_{Chinaj}$ 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.

# 5 Empirical Results

**Variance.** Table 3 presents results of equation (6) for the variance of the distribution of income growth. Column (1) shows the most simple OLS specification and indicates that an increase in \$1000 per worker in $\Delta IP_r$ increases the variance of one, three, and five-year income growth by 0.0496, 0.0804, and 0.107 respectively. In column (2), we add all sets of controls, as specified in the previous section. The estimated results decrease to 0.0095, 0.0246, and 0.0342, respectively, revealing the importance of adding the covariates.

Table 3: Effect of Trade Shock on Variance of Income Growth

| | OLS | | IV | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | | | $V[\Delta^5 y^i_{r,2015}]$ | | | |
| $\Delta IP_r$ | 0.107*** | 0.0342*** | 0.104*** | 0.0445*** | 0.0391*** | 0.0435*** |
| | (0.0150) | (0.00699) | (0.0139) | (0.00560) | (0.00509) | (0.00613) |
| | | | $V[\Delta^3 y^i_{r,2015}]$ | | | |
| $\Delta IP_r$ | 0.0804*** | 0.0246*** | 0.0779*** | 0.0329*** | 0.0284*** | 0.0324*** |
| | (0.0118) | (0.00628) | (0.0108) | (0.00502) | (0.00483) | (0.00545) |
| | | | $V[\Delta^1 y^i_{r,2015}]$ | | | |
| $\Delta IP_r$ | 0.0496*** | 0.00954* | 0.0468*** | 0.0168*** | 0.0130*** | 0.0164*** |
| | (0.00842) | (0.00556) | (0.00754) | (0.00415) | (0.00395) | (0.00510) |
| Region Controls in 2000 | | Yes | | Yes | Yes | Yes |
| $V[\Delta^n y^i_{r,2000}]$ | | Yes | | | Yes | Yes |
| Geographic Area FE | | Yes | | | | Yes |
| Observations | 503 | 503 | 503 | 503 | 503 | 503 |
| 1st Stage F-Stat | | | 402.49 | 406.85 | 409.95 | 300.29 |

*Notes:* This table estimates the impact of import penetration $\Delta IP_r$ on the variance of five ($V[\Delta^5 y^i_{r,2015}]$), three ($V[\Delta^3 y^i_{r,2015}]$ and one-year ($V[\Delta^1 y^i_{r,2015}]$) income growth. Income growth is calculated between 2015 and 2015 - $n$, where $n = 5, 3$ and 1. Region Controls in 2000 include: workers employed in the formal sector, the share of workers with high school and less of high school education, the size of the local workforce, the share of workers employed in informal jobs, the proportion of rural residents, the share of each region's workforce employed in agricultural, extractive and manufacturing sectors and a cubic polynomial of income per capita. The control $m[\Delta^1 y^i_{r,2000}]$ is the baseline value of the one-year income growth. The five Brazilian Macro-regions are North, Northeast, Central-West, Southeast and South. Standard errors in parenthesis are clustered at the mesoregion-level (130 units). Regressions are weighted by the share of the local labor force in 2000. *** p<0.01, ** p<0.05, * p<0.1.

In columns (3) to (6), we present results from the instrumental-variable framework described in Section 4. Column (3) displays the estimated coefficients without covariates and results are very similar to the OLS estimation without controls of column (1). Column (4) includes a full set of local labor market controls in the baseline year: mean age of workers employed in the formal sector, the share of workers with high school and less of high school education, the size of the local work-force, the share of workers employed in informal jobs, the proportion of rural residents, a cubic polynomial of income per capita and the share of each region's workforce employed in agricultural, extractive and manufacturing sectors in

2000. As argued before, by including these covariates, we compare regions with the same economic structure and sectoral composition, but that differ in product or industry specialization *within* these broad sectors. As in the OLS specification, the inclusion of these covariates is important and coefficients reduce significantly in terms of magnitude. However, they are still economically meaningful and statistically significant at a 1% level. As shown in column (4), \$1000 per worker rise in import penetration increases the variance of five, three, and one-year income growth by 0.0445, 0.0329, and 0.0168.

Then, column (5) includes the control for the baseline value of the variance of one-year income growth and column (6) a set of geographic area fixed effects. The results of both specifications do not differ substantially from column (4). A comparison between IV (column 6) and OLS (column 2) estimates with a full set of controls show that the OLS estimation is slightly downward biased. Under our preferred specification (column 6), an increase in a \$1000 per worker in $\Delta IP_r$ increases the variance of five, three, and one-year income growth by 0.0435, 0.0324, and 0.0164. These figures represent an increase of around 6.8%, 6.1%, and 4.3% if compared to the national mean values in the baseline year. Importantly, in all the specifications of Table 2, the effects of $\Delta IP_r$ on $V[\Delta^5 y^i_{r,2015}]$ are larger than the effects on $V[\Delta^3 y^i_{r,2015}]$ and $V[\Delta^1 y^i_{r,2015}]$. As discussed in section 2, given the cumulative nature of the variance of income growth, these results suggest that import penetration has increased both the persistent and the transitory risk. Moreover, given the stability of the coefficients presented in columns (4) to (6), in the remaining of the paper, we show only the results for the most robust specification (column 6). Additional results are available under request.

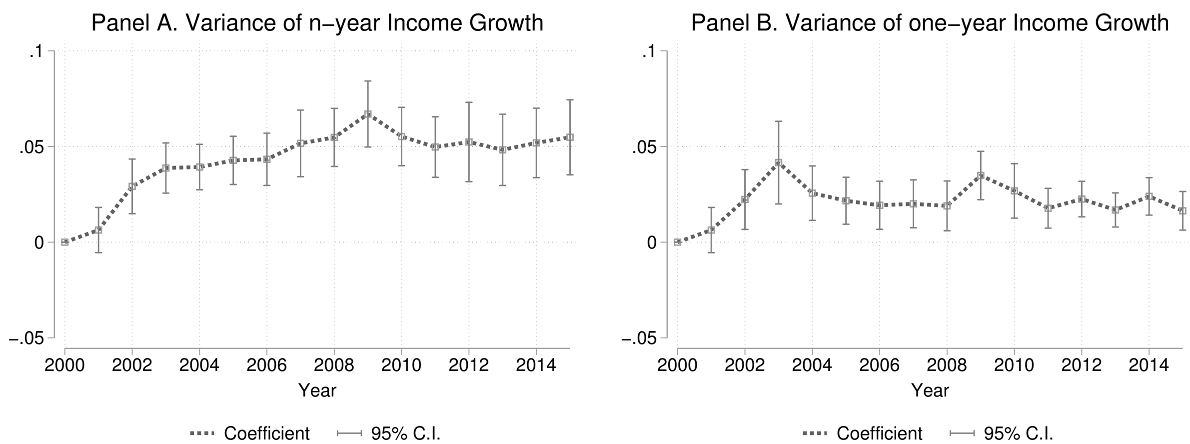
**Dynamic Assessment of Persistent and Transitory Idiosyncratic Shocks.** In this subsection, we exploit further the cumulative structure of the variance of income growth to study whether the idiosyncratic risk is explained mostly by its persistent or transitory components. Through the lens of the stochastic process outlined in Section 2, the income difference between $t$ and $t-n$ is the sum of the history of persistent shocks between these periods and the two transitory shocks in time $t$ and $t-n$ (Equation (3)). This implies that the variance of income growth has a cumulative structure: as $n$ increases, the variance of $\Delta^n y_t$ grows larger, as long the variances of transitory shocks are time-invariant.

Intuitively, it also means that if import penetration has a stronger effect on the permanent risk, the variance of $\Delta^n y_t$ will increase *faster* with $n$ in regions highly affected by trade competition.[24] To test this argument, we estimate the baseline model on the variance of

[24]One can see that by taking the difference between $n$ and $n-1$ in equation (3): $V(\Delta^n y_{r,t}) - V(\Delta^{n-1} y_{r,t-1}) = \sigma^2_{\eta,t} + \sigma^2_{\varepsilon,t} - \sigma^2_{\varepsilon,t-1}$. Hence, the final argument lies on two assumptions. First, it requires that the persistent shock is fully permanent ($\rho = 1$). Second, it lies on the assumption that the effect on the transitory shock is constant across time. If $\sigma^2_{\varepsilon,t} = \sigma^2_{\varepsilon,t-1}$, the difference of the variances between $n$

$n$-year income growth starting in 2001 (where $n = 1$) and progressively increasing $n$ until 2015 ($n = 15$). Panel A in Figure 4 plots the coefficients for the estimated regressions. The coefficients become progressively larger with time, peaking at 0.05 in 2009 and remaining relatively constant afterwards. The coefficients become gradually more positive from 2003 to 2009, which were exactly the years in which our trade-exposure measure grew faster (See Figure A.1).

Figure 4: Estimated Coefficient for the Variance of $n$-year and one-year Income Growth




*Notes:* Panel A plots the impact of import penetration $\Delta IP_r$ on the variance of $n$-year income growth, $V[\Delta^n y^i_{r,t+n}]$ from t=2001 ($n = 1$) to t=2015 ($n = 15$), while Panel B plots the impact of $\Delta IP_r$ on the variance of one-year income growth, $V[^1 y^i_{r,t}]$ from t=2001 ($n = 1$) to t=2015 ($n = 1$). Regressions are estimated through the instrumental variable approach and include all covariates, as in Column (6) of Table 3. The 95% confidence intervals are plotted.

Even though Panel A shows that the estimated coefficient on the variance of the $n$-year income growth distribution increases over time, we cannot attribute the effect only to the permanent shock. It could be, for instance, that the effect on the transitory shock is also increasing over time. To rule out this possibility, we estimate the baseline specification using the variance of one-year growth as the dependent variable in all periods, and plot the coefficients in Panel B. The estimates increase until 2003 and, after a slight decrease, remain constant for the rest of the period at around the 0.02 level. Remember that each one-year income-growth variance at time $t$ encapsulates the variance of the permanent shock at $t$ and the variances of the transitory shock at $t$ and $t-1$. Thus, the relative stability of the coefficients in the period 2002-2015 provides convincing suggestive evidence that the transitory shock is time-invariant and that the increase in the idiosyncratic risk of affected

and $n-1$ fully identifies the permanent component. Both assumptions are somewhat restrictive, so we take this result as merely illustrative. We pursuit a fully transitory-persistent decomposition in Section 7.

local labor markets can be mostly attributed to the permanent risk.

**Dispersion.** Table 4 shows the results of our baseline specification for different measures of dispersion of the distribution of five, three, and one-year income growth. In general, the effect of import penetration on the P9010 follows the same tendency as the variance. The coefficients are positive, significant at the 1% level, and larger for the five-year income growth distribution. A \$1000 increase per worker in $\Delta IP_r$ increases the difference between the $90^{th}$ and the $10^{th}$ percentile of $\Delta^5 y^i_{r,2015}$, $\Delta^3 y^i_{r,2015}$ and $\Delta^1 y^i_{r,2015}$ by 9.2, 7.4, and 6.2 percentage points. Note that the interquartile range in import penetration growth between 2000 and 2015 was approximately \$500 per worker, meaning that the dispersion of the five-year labor income growth between 2010 and 2015 of a region in the $75^{th}$ percentile of $\Delta IP$ increased by 4.6 percentage points more than the dispersion of a region in the $25^{th}$ percentile of the shock.

Apart from being robust to outliers, another advantage of the $P9010$ is that the total dispersion is the sum of the dispersion in the upper tail, $P9050 \equiv P90 - P50$, and the dispersion in the lower tail, $P5010 \equiv P50 - P10$. To decompose the effect of import penetration on dispersion, we run our baseline specification using both the $P9050$ and the $P5010$ as the dependent variable.[25] The results from Table 4 display a clear message: the impact of $\Delta IP_r$ on dispersion is largely concentrated in the lower tail. Roughly, the effect on the $P5010$ accounts for 76% (0.0697/0.0915), 80% (0.0588/0.0736) and 69% (0.0427/0.0620) of the total effect of $\Delta IP_r$ on the P9010 of $\Delta^5 y^i_{r,2015}$, $\Delta^3 y^i_{r,2015}$ and $\Delta^1 y^i_{r,2015}$ respectively.

**Asymmetry and Tails.** Although the dispersion is a good starting point to understand how trade affects the idiosyncratic income growth, it may still hide important effects if the distribution deviates from normality. For instance, even if trade shocks had no effects on the dispersion, earnings risk could increase if these shocks generated a negative impact on skewness. Table 5 outlines the results for different measures related to the asymmetry and tails of the distribution, namely: the Kelley skewness, the share of individuals with negative and positive income changes of 50% or more ($P(\Delta^n y^i_t < -0.5)$ and $P(\Delta^n y^i_t > 0.5)$), and the Crow-Siddiqui kurtosis of one, three and five-year income growth distributions.

Regarding the asymmetry, an increase in import penetration has a negative and significant effect on the skewness of the distribution. Remember that we can re-write equation (4) as $\mathcal{S}_K/2 + 0.5 = (P90 - P50)/(P90 - P10)$. Taking this formula, results show that an

[25] Note that the control $m[\Delta^1 y^i_{r,2000}]$ is set to be equal to $P9050[\Delta^1 y^i_{r,2000}]$ in the regression for the P9050 and $P5010[\Delta^1 y^i_{r,2000}]$ in the regression for the P5010. Therefore, the sum of the two coefficients is not exactly the coefficient of the regression on the $P9010$. If the covariates were exactly the same, the coefficients would perfectly add up.

Table 4: Effect of Trade Shock on Dispersion of Income Growth

| | Variance | P9010 | P9050 | P5010 |
|---|---|---|---|---|
| | $m[\Delta^5 y^i_{r,2015}]$ | | | |
| $\Delta IP_r$ | 0.0435*** | 0.0915*** | 0.0212** | 0.0697*** |
| | (0.00613) | (0.0142) | (0.00936) | (0.0127) |
| | $m[\Delta^3 y^i_{r,2015}]$ | | | |
| $\Delta IP_r$ | 0.0324*** | 0.0736*** | 0.0141 | 0.0588*** |
| | (0.00545) | (0.0158) | (0.0108) | (0.0146) |
| | $m[\Delta^1 y^i_{r,2015}]$ | | | |
| $\Delta IP_r$ | 0.0164*** | 0.0620*** | 0.0183** | 0.0427*** |
| | (0.00510) | (0.0220) | (0.00917) | (0.0142) |
| Region Controls in 2000 | Yes | Yes | Yes | Yes |
| $m[\Delta^1 y^i_{r,2000}]$ | Yes | Yes | Yes | Yes |
| Geographic Area FE | Yes | Yes | Yes | Yes |
| Observations | 503 | 503 | 503 | 503 |
| 1st Stage F-Stat | 300.29 | 299.94 | 302.27 | 301.09 |

*Notes:* Using the IV framework, this table estimates the impact of import penetration $\Delta IP_r$ on the dispersion of five ($\Delta^5 y^i_{r,2015}$), three ($\Delta^3 y^i_{r,2015}$) and one-year ($\Delta^1 y^i_{r,2015}$) income growth. Income growth is calculated between 2015 and 2015 - $n$, where $n = 5, 3$ and 1. Region Controls in 2000 include: workers employed in the formal sector, the share of workers with high school and less of high school education, the size of the local workforce, the share of workers employed in informal jobs, the proportion of rural residents, the share of each region's workforce employed in agricultural, extractive and manufacturing sectors and a cubic polynomial of income per capita. The control $m[\Delta^1 y^i_{r,2000}]$ is the baseline value of the one-year income growth respective moment. The five Brazilian Macro-regions are North, Northeast, Central-West, Southeast and South. Standard errors in parenthesis are clustered at the mesoregion-level (130 units). Regressions are weighted by the share of the local labor force in 2000. *** p<0.01, ** p<0.05, * p<0.1.

increase of \$1000 per worker in $\Delta IP$ reduces the share of the $P9010$ accounted by the $P9050$ in 1.8, 1.7 and 1.2 p.p for $\Delta^5 y^i_{r,2015}$, $\Delta^3 y^i_{r,2015}$ and $\Delta^1 y^i_{r,2015}$ respectively. In another example, suppose a region with a complete symmetrical distribution of the five-year income growth ($\mathcal{S}_K = 0$ and $P9050/P9010 = 50\%$) increases its trade import exposure by \$1000 per worker. Then, the estimated coefficient in Table 5 implies that the ratio $P9050/P9010$ would go from 50% to around 48.2% ($\mathcal{S}_K = -3.55$ and $P9050/P9010 = 48.2\%$). These results suggest that the distribution of income growth becomes more negatively skewed.

While the results in Table 5 show that an increase in import penetration leads to a rise in the share of individuals receiving large shocks in both tails, the increase in the proportion of individuals suffering negative income shocks lower than -50% is roughly two times larger than the coefficient on the proportion of workers receiving positive shocks larger than 50%.

Table 5: Effect of Trade Shock on Asymmetry and Tails of Income Growth

| | Skewness | $P(\Delta^n y_t^i > 0.5)$ | $P(\Delta^n y_t^i < -0.5)$ | Kurtosis |
|---|---|---|---|---|
| | | $m[\Delta^5 y_{r,2015}^i]$ | | |
| $\Delta IP_r$ | -0.0355** | 0.00652*** | 0.0101*** | -0.0107 |
| | (0.0142) | (0.00190) | (0.00309) | (0.120) |
| | | $m[\Delta^3 y_{r,2015}^i]$ | | |
| $\Delta IP_r$ | -0.0330** | 0.00485*** | 0.00821*** | -0.0945 |
| | (0.0166) | (0.00178) | (0.00252) | (0.143) |
| | | $m[\Delta^1 y_{r,2015}^i]$ | | |
| $\Delta IP_r$ | -0.0232* | 0.00370** | 0.00636*** | -0.176 |
| | (0.0135) | (0.00161) | (0.00218) | (0.343) |
| Region Controls in 2000 | Yes | Yes | Yes | Yes |
| $m[\Delta^1 y_{r,2000}^i]$ | Yes | Yes | Yes | Yes |
| Geographic Area FE | Yes | Yes | Yes | Yes |
| Observations | 503 | 503 | 503 | 503 |
| 1st Stage F-Stat | 302.65 | 300.63 | 298.27 | 298.98 |

*Notes:* Using the IV framework, this table estimates the impact of import penetration $\Delta IP_r$ on the asymmetry and tails of the income growth distribution. Income growth is calculated between 2015 and 2015 - $n$, where $n = 5, 3$ and 1. Skewness refers to the Kelley skewness and kurtosis refers to Crow-Siddiqui kurtosis. Region Controls in 2000 include: workers employed in the formal sector, the share of workers with high school and less of high school education, the size of the local workforce, the share of workers employed in informal jobs, the proportion of rural residents, the share of each region's workforce employed in agricultural, extractive and manufacturing sectors and a cubic polynomial of income per capita. The control $m[\Delta^1 y_{r,2000}^i]$ is the baseline value of the one-year income growth respective moment. The five Brazilian Macro-regions are North, Northeast, Central-West, Southeast and South. Standard errors in parenthesis are clustered at the mesoregion-level (130 units). Regressions are weighted by the share of the local labor force in 2000. *** p<0.01, ** p<0.05, * p<0.1.

The estimated coefficient implies that an \$1000 rise in $\Delta IP_r$ increases the share of individuals receiving a large negative income change by 1, 0.8 and 0.6 percentage points for $\Delta^5 y_{r,2015}^i$, $\Delta^3 y_{r,2015}^i$ and $\Delta^1 y_{r,2015}^i$ respectively.

Finally, we found no results of $\Delta IP_r$ on the Crow-Siddiqui kurtosis. This suggests that the ratio between the dispersion on the tails ($P97.5 - P2.5$) and the interquartile range ($P75 - P25$) is not associated with changes in our measure of trade exposure. Again, this is not inconsistent with the positive effects found in the share of large negative and positive income changes, since the increase in the share does not necessarily indicate changes in the *ratio* of differences in centiles.

**Mean.** Although the effect on the average income growth has been widely studied and is not the main focus of the paper, we find it useful to compare our analysis with previous results in the literature. To make our estimates more comparable with other studies, in this subsection alone, we retain the time effects and clean income and wages from age effects only. Hence, we define the average log yearly income growth of local labor market $r$ as $\mu_r[\Delta^n y_t^i]$, where $\Delta^n y_t^i$ is the residual real earnings growth (net of age effects) of individual $i$ between $t$ and $t-n$. Moreover, we also do the same regression with hourly wages $\mu_r[\Delta^n w_t^i]$.

Table 6 shows that a \$1000 per worker increase in import penetration yields a decrease in the growth rate of income of 4.4 percentage points between 2000 and 2015 (column 1) and 2.4 percentage points between 2010 and 2015 (column 2). Coefficients for wages in columns (3) and (4) follow a similar pattern. Results are relatively in line with Costa et al. (2016), who find that in regions experiencing a \$1000 rise in imports per worker, individuals' average wages rose from 0.58 to 4.42 percentage points more slowly over the course of the 2000-2010 decade (although in their preferred specification, the estimate is statistically insignificant). When focusing on manufacturing workers, the authors find that a \$1000 rise in imports per worker decreases the average growth rate of wages by 2.93 to 7.48 percentage points, with significant coefficients in all specifications.

The fact that both papers find a negative impact of important exposure on income growth is reassuring, even if we perform conceptually different exercises. Costa et al. (2016) use the full population Census from 2000 and 2010 and estimate the impact of trade on wages of formal and informal workers. Although they control for composition, their effects on wages' might still suffer from selection issues. Our results, instead, is cleaned of composition effects, as we rely on the panel data dimension of RAIS and compute income growth for each individual. In contrast, we can only analyze the impact of trade on wages of formally employed individuals, abstracting from a substantial part of the Brazilian labor market composed of informal workers. Additionally, our sample of formal workers oversamples individuals working in manufacturing, as shown in Table 1. Thus, it is reasonable that our estimates lie in between their estimates for all workers and the ones for individuals employed in the manufacturing sector only.

# 6 Sources of Dispersion and Tails of Labor Income Growth

In the previous section, we argued that trade shocks change the distribution of income growth. Now, we explore possible explanations for these changes. For the sake of simplicity, the tables of this section contain results for the distribution of five and one-year changes. Results for the three-year changes are available upon request.

Table 6: Effect of Trade Shock on Mean of Log of Labor Income Growth and Log of Hourly Wage Growth

| | (1) $\mu[\Delta^{15} y^i_{r,2015}]$ | (2) $\mu[\Delta^{5} y^i_{r,2015}]$ | (3) $\mu[\Delta^{15} w^i_{r,2015}]$ | (4) $\mu[\Delta^{5} w^i_{r,2015}]$ |
|---|---|---|---|---|
| $\Delta IP_r$ | -0.0443** | -0.0237*** | -0.0372** | -0.0228*** |
| | (0.0212) | (0.00642) | (0.0174) | (0.00472) |
| Observations | 503 | 503 | 503 | 503 |
| 1st Stage F-Stat | 301.47 | 301.47 | 289.91 | 289.91 |
| Region Controls in 2000 | Yes | Yes | Yes | Yes |
| $\mu[\Delta^5 y^i_{r,2000}]$ | Yes | Yes | | |
| $\mu[\Delta^5 w^i_{r,2000}]$ | | | Yes | Yes |
| Geographic Area FE | Yes | Yes | Yes | Yes |

*Notes:* Using the IV framework, this table estimates the impact of import penetration $\Delta IP_r$ on the mean of Labor Income $\mu[\Delta^n y^i_{r,t}]$ and Hourly Wages' Growth $\mu[\Delta^n w^i_{r,t}]$. Income growth is calculated between 2015 and 2015 - $n$. Region Controls in 2000 include: workers employed in the formal sector, the share of workers with high school and less of high school education, the size of the local workforce, the share of workers employed in informal jobs, the proportion of rural residents, the share of each region's workforce employed in agricultural, extractive and manufacturing sectors and a cubic polynomial of income per capita. The control $m[\Delta^5 y^i_{r,2000}]$ is the baseline value of the five-year income growth respective moment. The five Brazilian Macro-regions are North, Northeast, Central-West, Southeast and South. Standard errors in parenthesis are clustered at the mesoregion-level (130 units). Regressions are weighted by the share of the local labor force in 2000. *** p<0.01, ** p<0.05, * p<0.1.

**Hours and Wages.** Thus far, we have considered the log annual labor income as the outcome of a single stochastic process. In reality, the labor income can be decomposed as the sum of hourly wages $w^i_t$ and annual hours worked $h^i_t$: $y^i_t = w^i_t + h^i_t$.[26] Whether changes in yearly income come from wages or hours is important, as it reflects which type of economic shocks and choices (promotions, job/occupation/industry switching, nonemployment spells, health shocks, etc.) drive the income dynamics. Particularly, we can decompose the variance of income changes in three terms:

$$\begin{aligned} V(\Delta^n y^i_t) &= V(\Delta^n w^i_t + \Delta^n h^i_t) \\ &= V(\Delta^n w^i_t) + V(\Delta^n h^i_t) + 2 \times COV(\Delta^n w^i_t, \Delta^n h^i_t), \end{aligned} \tag{9}$$

where the first is the variance of hourly-wage changes, the second is the variance of annual-hours changes, and the last is the covariance between the two. To test which of the

[26]In practice annual hours can be decomposed into weeks worked (extensive margin) and weekly hours (intensive margin). However, due to data limitations, we refrain to carry on this decomposition. RAIS reports only contract hours and we cannot observe fluctuations in weekly hours within the same employment spell. In practice, this means that most variations in annual hours are explained by periods of nonemployment.

terms is responsible for the increase in dispersion of annual income growth, we estimate our baseline specification including each component as the dependant variable.[27]

Table 7: Effect of Trade Shock on Variance of Wages, Hours and Covariance between Wage and Hours for Five and One-year Growth Distributions

| | (1) $V[\Delta^5 w^i_{r,2015}]$ | (2) $V[\Delta^5 h^i_{r,2015}]$ | (3) $COV[\Delta^5 w^i_{r,2015}, \Delta^5 h^i_{r,2015}]$ |
|---|---|---|---|
| $\Delta IP_r$ | 0.00932 | 0.0241*** | 0.00747 |
| | (0.00569) | (0.00878) | (0.00697) |
| | $V[\Delta^1 w^i_{r,2015}]$ | $V[\Delta^1 h^i_{r,2015}]$ | $COV[\Delta^1 w^i_{r,2015}, \Delta^1 h^i_{r,2015}]$ |
| $\Delta IP_r$ | 0.00465** | 0.0132** | 0.000722 |
| | (0.00216) | (0.00523) | (0.00228) |
| Region Controls in 2000 | Yes | Yes | Yes |
| $V[\Delta^1 w^i_{r,2000}]$ | Yes | | |
| $V[\Delta^1 h^i_{r,2000}]$ | | Yes | |
| $COV[\Delta^1 w^i_{r,2000}, \Delta^1 h^i_{r,2000}]$ | | | Yes |
| Geographic Area FE | Yes | Yes | Yes |
| Observations | 503 | 503 | 503 |
| 1st Stage F-Stat | 302.52 | 300.28 | 300.79 |

*Notes:* Using the IV framework, this table estimates the impact of import penetration $\Delta IP_r$ on the variance of five and one-year wages and hours growth, and on the covariance between the two. The growth rate is calculated between 2015 and 2015 - $n$, where $n = 5$ and 1. Region Controls in 2000 include: workers employed in the formal sector, the share of workers with high school and less of high school education, the size of the local workforce, the share of workers employed in informal jobs, the proportion of rural residents, the share of each region's workforce employed in agricultural, extractive and manufacturing sectors and a cubic polynomial of income per capita. The control $V[\Delta^1 w^i_{r,2000}]//V[\Delta^1 h^i_{r,2000}]//COV[\Delta^1 w^i_{r,2000}, \Delta^1 h^i_{r,2000}]$ is the baseline value of the one-year growth for each outcome. The five Brazilian Macro-regions are North, Northeast, Central-West, Southeast and South. Standard errors in parenthesis are clustered at the mesoregion-level (130 units). Regressions are weighted by the share of the local labor force in 2000. *** p<0.01, ** p<0.05, * p<0.1.

The results are summarized in Table 7. An increase of \$1000 per worker in $\Delta IP$ increases the variance of the distribution of five and one-year changes in annual hours by 0.0241 and 0.0132. In comparison, the associated coefficients of the variance of changes in hourly wages are only 0.00932, and 0.00465, respectively. The effects on the covariance are positive but statistically indistinguishable from zero. This shows that the impact of import penetration on the variance of idiosyncratic earnings growth can be largely explained by the increase in

[27] We apply the same treatment as for annual labor income, which means that we first calculate the residuals of a regression of log wages or log hours on age and time fixed effects and then calculate the relevant moments. This indicates that, although very similar, the regression coefficients are not exactly additive as stated in the decomposition.

the volatility in hours worked annually, with a minor effect on hourly wages.

Table 8: Effect of Trade Shock on Right and Left Tail Dispersion of the Five and One-year Wage and Hours Growth Distributions

| | P9010 | P9050 | P5010 | P9010 | P9050 | P5010 |
|---|---|---|---|---|---|---|
| | | $m[\Delta^5 w^i_{r,2015}]$ | | | $m[\Delta^5 h^i_{r,2015}]$ | |
| $\Delta IP_r$ | 0.0269*** | -0.00277 | 0.0299*** | 0.0455** | 0.0190* | 0.0253 |
| | (0.00957) | (0.0113) | (0.0107) | (0.0216) | (0.00966) | (0.0201) |
| | | $m[\Delta^1 w^i_{r,2015}]$ | | | $m[\Delta^1 h^i_{r,2015}]$ | |
| $\Delta IP_r$ | 0.00609 | -0.00762 | 0.0133* | 0.0464* | 0.0249* | 0.0227 |
| | (0.00866) | (0.00496) | (0.00708) | (0.0252) | (0.0129) | (0.0142) |
| Region Controls in 2000 | Yes | Yes | Yes | Yes | Yes | Yes |
| $m[\Delta^1 w^i_{r,2000}]$ | Yes | Yes | Yes | | | |
| $m[\Delta^1 h^i_{r,2000}]$ | | | | Yes | Yes | Yes |
| Geographic Area FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 503 | 503 | 503 | 503 | 503 | 503 |
| 1st Stage F-Stat | 300.90 | 300.69 | 300.73 | 301.98 | 301.07 | 302.20 |

*Notes:* Using the IV framework, this table estimates the impact of import penetration $\Delta IP_r$ on the P9010, P9050 and P5010 of five and one-year wages and hours growth. The growth rate is calculated between 2015 and 2015 - $n$, where $n = 5$ and 1. Region Controls in 2000 include: workers employed in the formal sector, the share of workers with high school and less of high school education, the size of the local workforce, the share of workers employed in informal jobs, the proportion of rural residents, the share of each region's workforce employed in agricultural, extractive and manufacturing sectors and a cubic polynomial of income per capita. The control $m[\Delta^1 w^i_{r,2000}]//m[\Delta^1 h^i_{r,2000}]$ is the baseline value of the one-year wages/hours growth. The five Brazilian Macro-regions are North, Northeast, Central-West, Southeast and South. Standard errors in parenthesis are clustered at the mesoregion-level (130 units). Regressions are weighted by the share of the local labor force in 2000. *** p<0.01, ** p<0.05, * p<0.1.

Shifting to each tail individually, Table 8 shows the effect of $\Delta IP$ on the $P9010$, $P9050$ and $P5010$ for wages and hours. Again, the effect on the overall dispersion of hours is roughly 2 to 4 times larger than the effect on wages. Nevertheless, once we unpack the overall dispersion, we find that the effect of $\Delta IP$ on the $P9010$ of the distribution of wage growth is accounted exclusively by the lower tail. In contrast, the effect on the $P9010$ of the distribution of growth in hours is divided equally between both tails. This could be rationalized by an increase in industry or occupation switching that entails some human capital loss and, thus, lower wages, and would go in line with the literature that portrays the existence of scaring effects on wages following a job displacement (Jacobson et al. (1993) and Davis and von Wachter (2011)), but little or no scaring effects on hours worked (Ruhm (1991) and Altonji et al. (2013)).[28]

[28]Our smaller results on hours worked are, however, suggestive only, since we focus on workers highly

**Job and Industry Switching.** The trade literature emphasizes the role of labor reallocation across employers and industries after a trade shock. Does reallocation explain the changes observed in the distribution of income growth in our setting? To answer this question, we first study whether the trade shock increases the fraction of job and industry switchers. A job (industry) switcher is defined as an individual employed in a different firm (industry) in time $t$ and in $t-n$.[29] In our national sample, between 2000-1999, the fraction of job and industry switchers was 16.6% and 10.4% respectively, while between 2000-1995 this fraction was 49.6% and 33.2%. Recent literature has shown that the distribution of income growth of job switchers is more disperse than the one of non-switchers (Halvorsen et al. (2020) and Guvenen et al. (2019)). This is also true in our sample. Between 2000-1995, the variance and the P9010 of job switchers are 1.01 and 2.27. For the non-switchers, the values are considerably smaller: are 0.27 and 1.01. Thus, a larger fraction of switchers would imply a more disperse distribution.

Table 9: Effect of Trade Shock on the Fraction of Job and Industry Switchers

| | *Fraction of Job Switchers* | | *Fraction of Ind. Switchers* | |
|---|---|---|---|---|
| | $n=5$ | $n=1$ | $n=5$ | $n=1$ |
| $\Delta IP_r$ | 0.0140* | 0.00180 | 0.0258*** | 0.00753** |
| | (0.00783) | (0.00360) | (0.00950) | (0.00362) |
| Observations | 503 | 503 | 503 | 503 |
| 1st Stage F-Stat | 301.60 | 301.60 | 315.64 | 315.64 |
| Region Controls in 2000 | Yes | Yes | Yes | Yes |
| Job Switchers (2000-1999) | Yes | Yes | | |
| Ind. Switchers (2000-1999) | | | Yes | Yes |
| Geographic Area FE | Yes | Yes | Yes | Yes |

*Notes:* Using the IV framework, this table estimates the impact of import penetration $\Delta IP_r$ on the fraction of job and industry switchers between 2015 and 2015-$n$. Region Controls in 2000 include: workers employed in the formal sector, the share of workers with high school and less of high school education, the size of the local workforce, the share of workers employed in informal jobs, the proportion of rural residents, the share of each region's workforce employed in agricultural, extractive and manufacturing sectors and a cubic polynomial of income per capita. The five Brazilian Geographic Areas are North, Northeast, Central-West, Southeast and South. Standard errors in parenthesis are clustered at the mesoregion-level (130 units). Regressions are weighted by the share of the local labor force in 2000. *** p<0.01, ** p<0.05, * p<0.1.

Table 9 shows that import penetration has a positive effect on the fraction of job and

attached to the labor market and might, thus, underestimate scaring effects on employment.

[29] Recall that each individual is assigned a unique employer and industry per year. In the case the individual had multiple employment spells, the industry and employer with the largest spell is assigned. In the case of ties, the largest total labor income is used as a tie-breaker.

industry switchers. Results are larger for the 5-year differences and for industry switchers. An increase of $1000 in $\Delta IP_r$ increases the fraction of job and industry switchers by 1.4 and 2.6 percentage points when $n = 5$. Importantly, it is unlikely that these changes entirely explain the overall effect of $\Delta IP_r$ on dispersion observed in Table 4. A simple back of the envelope calculation suggests that if the variance of switchers and non-switchers remained constant on their respective baseline values in 1995-2000, the increase in 1.4 p.p in the fraction of job switchers would have an impact of $0.014 \times (1.01 - 0.27) = 0.01$ on the overall variance, less than a fourth of the coefficient reported in Table 4. Similarly, the increase in the fraction of industry switchers would raise the variance by $0.0258 \times (1.22 - 0.34) = 0.0227$, roughly half of the coefficient on the overall variance.

We then analyze the impact of import penetration on the distribution of income growth of switchers and stayers separately. Table 10 shows that a shock of $1000 in $\Delta IP_r$ increases the variance of the five-year income growth of job switchers by 0.0533, seven times the magnitude of non-switchers. The effect on industry switchers is 0.0444, 9.5 times more than for non-switchers. Results for the variance of one-year income growth follow a similar pattern, although with a smaller gap in the magnitudes. Results are also robust to the use of other measures of dispersion, as seen in Table A.6. These findings are consistent with the large effects found on the variance of hours worked in Table 8. The individuals that switch jobs often go through unemployment spells and are precisely the ones who experience larger variability in hours worked. Thus, our results indicate that job and industry switchers are the workers most affected by trade shocks. In Table A.7, we present results of the impact of import penetration on the distribution of hours and wages of switchers and non-switchers separately, and confirm that the main mechanisms behind the increase in dispersion of idiosyncratic income growth are the changes in hours worked of job and industry switchers.

**Tails.** Finally, Table 11 confirms that the impact of import penetration on the extreme income changes can also be rationalized by an increase in job and industry switches. A shock of $1000 in $\Delta IP_r$ increases the fraction of switchers that *also* experience a large positive income change ($\Delta^n y_t^i > 0.5$) by 0.74 percentage points and the fraction that *also* experience a large negative income change ($\Delta^n y_t^i < -0.5$) by 0.88 percentage points. These numbers represent an increase of 6% and 7.5% compared to national baseline values computed between 1995 and 2000 (12.4% and 11.7%). In contrast, there are no effects on non-switchers. Results are similar for industry switchers.

Table 10: Effect of Trade Shock on the Variance of the Distribution of Income Growth: Job and Industry Switchers and Stayers

| | *Job Switchers* | | *Ind. Switchers* | |
|---|---|---|---|---|
| | $V[\Delta^5 y^i_{r,2015}]$ | $V[\Delta^1 y^i_{r,2015}]$ | $V[\Delta^5 y^i_{r,2015}]$ | $V[\Delta^1 y^i_{r,2015}]$ |
| $\Delta IP_r$ | 0.0533*** | 0.0473*** | 0.0444*** | 0.0291*** |
| | (0.0126) | (0.00949) | (0.0139) | (0.00945) |
| Observations | 491 | 491 | 474 | 474 |
| 1st Stage F-Stat | 284.75 | 284.75 | 280.77 | 280.77 |
| | *Job Stayers* | | *Ind. Stayers* | |
| | $V[\Delta^5 y^i_{r,2015}]$ | $V[\Delta^1 y^i_{r,2015}]$ | $V[\Delta^5 y^i_{r,2015}]$ | $V[\Delta^1 y^i_{r,2015}]$ |
| $\Delta IP_r$ | 0.00760** | 0.0102*** | 0.00468 | 0.00990** |
| | (0.00380) | (0.00327) | (0.00426) | (0.00386) |
| Observations | 494 | 494 | 501 | 501 |
| 1st Stage F-Stat | 298.40 | 298.40 | 300.97 | 300.97 |
| Region Controls in 2000 | Yes | Yes | Yes | Yes |
| $V[\Delta^1 y^i_{r,2000}]$ | Yes | Yes | Yes | Yes |
| Geographic Area FE | Yes | Yes | Yes | Yes |

*Notes:* Using the IV framework, this table estimates the impact of import penetration $\Delta IP_r$ on the variance of five ($\Delta^5 y^i_{r,2015}$), and one-year ($\Delta^1 y^i_{r,2015}$) income growth of job and industry switchers, and job and industry stayers. Income growth is calculated between 2015 and 2015 - $n$, where $n$ = 5 and 1. Region Controls in 2000 include: workers employed in the formal sector, the share of workers with high school and less of high school education, the size of the local workforce, the share of workers employed in informal jobs, the proportion of rural residents, the share of each region's workforce employed in agricultural, extractive and manufacturing sectors and a cubic polynomial of income per capita. The control $m[\Delta^1 y^i_{r,2000}]$ is the baseline value of the one-year income growth respective moment. The five Brazilian Macro-regions are North, Northeast, Central-West, Southeast and South. Standard errors in parenthesis are clustered at the mesoregion-level (130 units). Regressions are weighted by the share of the local labor force in 2000. Only regions with at least 100 individuals used to compute the moments are included. *** p<0.01, ** p<0.05, * p<0.1.

# 7 The Welfare Consequences of the Increase in Risk

In the previous section, we estimated the causal effect of the increase in import penetration following the China shock on the empirical distributions of income growth across Brazilian local labor markets. In this section, we use our causal estimates to quantify the welfare losses from the increase in risk from trade. We proceed in two steps.

First, we estimate two stochastic income processes augmented to account for higher-order risk. The first income process is estimated targeting empirical moments (i.e. P9010, $P(\Delta^n y^i_t < -0.5)$, etc.) of the distribution of income changes using the national sample

Table 11: Effect of Trade Shock on the Tails of the Distribution of Income Growth: Job and Industry Switchers and Stayers

| | Fraction with $\Delta^5 y_t^i > 0.5$ | | | | |
|---|---|---|---|---|---|
| | All | Job Switchers | Job Stayers | Ind. Switchers | Ind. Stayers |
| $\Delta IP_r$ | 0.00652*** | 0.00738*** | 0.000480 | 0.00953*** | -0.00213 |
| | (0.00190) | (0.00241) | (0.000830) | (0.00211) | (0.00163) |
| Observations | 503 | 503 | 503 | 503 | 503 |
| 1st Stage F-Stat | 300.63 | 299.87 | 294.52 | 308.62 | 293.98 |
| | Fraction with $\Delta^5 y_t^i < -0.5$ | | | | |
| | All | Job Switchers | Job Stayers | Ind. Switchers | Ind. Stayers |
| $\Delta IP_r$ | 0.0101*** | 0.00880*** | -0.00175* | 0.0107*** | -0.00399*** |
| | (0.00309) | (0.00268) | (0.000996) | (0.00261) | (0.00140) |
| Observations | 503 | 503 | 503 | 503 | 503 |
| 1st Stage F-Stat | 298.27 | 303.76 | 301.64 | 315.15 | 306.75 |
| Region Controls in 2000 | Yes | Yes | Yes | Yes | Yes |
| Fraction 1999-2000 | Yes | Yes | Yes | Yes | Yes |
| Geographic Area FE | Yes | Yes | Yes | Yes | Yes |

*Notes:* Using the IV framework, this table estimates the impact of import penetration $\Delta IP_r$ on the fraction of workers with large positive income growth ($\Delta^n y_t^i > 0.5$) or large negative income growth ($\Delta^n y_t^i < -0.5$) between 2015 and 2010 (Column All). The other columns portray results on the fraction of workers that, in addition of having large earnings changes, are also job/industry switcher/stayers. Region Controls in 2000 include: workers employed in the formal sector, the share of workers with high school and less of high school education, the size of the local workforce, the share of workers employed in informal jobs, the proportion of rural residents, the share of each region's workforce employed in agricultural, extractive and manufacturing sectors and a cubic polynomial of income per capita. The control *Fraction 1999-2000* is the baseline value of the one-year income growth respective moment. The five Brazilian Macro-regions are North, Northeast, Central-West, Southeast and South. Standard errors in parenthesis are clustered at the mesoregion-level (130 units). Regressions are weighted by the share of the local labor force in 2000. *** p<0.01, ** p<0.05, * p<0.1.

of workers from 1995 to 2000. This stochastic process captures the labor income risk in Brazil *before* the large trade shock from China. The second income process is estimated targeting the counterfactual moments of income growth implied by the causal estimates. The counterfactual moments are constructed by summing the empirical moments used in the previous estimation plus the (weighted) average increase of $\Delta IS_r$ and $\Delta XD_r$ from 2000 to 2015 times the estimated coefficients of the previous sections.[30]

Second, we input both the pre-China and the counterfactual income process in a standard partial equilibrium incomplete-markets model (Kaplan and Violante (2010) and De Nardi et al. (2020)) and compute the differences regarding welfare. We interpret this difference as the welfare cost of the increase in labor income risk caused by the China shock.

## 7.1 The Income Process

In light of the results established in the previous sections, we perform a full permanent-transitory decomposition of the idiosyncratic risk by estimating a stochastic income process. 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:

$$y_t^i = z_t^i + \varepsilon_t^i, \tag{10}$$

$$z_t^i = z_{t-1}^i + \eta_t^i, \tag{11}$$

$$\eta_t^i \sim \begin{cases} N(\mu_{\eta,1}, \sigma_{\eta,1}^2) & \text{with prob. } p_\eta \\ N(\mu_{\eta,2}, \sigma_{\eta,2}^2) & \text{with prob. } 1 - p_\eta \end{cases} \tag{12}$$

$$\varepsilon_t^i \sim \begin{cases} N(\mu_{\varepsilon,1}, \sigma_{\varepsilon,1}^2) & \text{with prob. } p_\varepsilon, \\ N(\mu_{\varepsilon,2}, \sigma_{\varepsilon,2}^2) & \text{with prob. } 1 - p_\varepsilon. \end{cases} \tag{13}$$

The econometric model includes a permanent component modeled as a unit root with iid innovations $\eta_t^i$ and an iid transitory innovation $\varepsilon_t^i$, both drown from a mixture of normal distributions.[31] The flexibility of the mixture of normal distributions allows the departure from the log-normal framework and is used to match both the transitory and permanent

[30] For example, the $P9010[\Delta^5 y_{2000}^i]$ is equal to 1.627. The post-China counterfactual P9010 is calculated as $P9010[\Delta^5 y_{CF}^i] = 1.627 + 0.467 \times 0.0915 + 0.562 \times 0.0049 = 1.67$, where 0.467 and 0.564 are the average increase of $\Delta IS_{rt}$ and $\Delta XD_{rt}$. In practice, most of the coefficients of $\Delta XD_{rt}$ are an order of magnitude smaller than the ones from $\Delta IS_{rt}$, and therefore are irrelevant for the estimation.

[31] Instead of a fully permanent, we also experiment using an AR(1) with persistence $\rho$. The estimated $\rho$ was close to unity, and the results were virtually the same.

higher-order moments. We restrict the mean of both the persistent and transitory innovations to zero: $E(\eta_t^i) = 0$ and $E(\varepsilon_t^i) = 0$. Hence, we estimate $\mu_{\eta,1}$ and $\mu_{\varepsilon,1}$ under the restriction of being greater or equal to zero, and recover $\mu_{\eta,2}$ and $\mu_{\varepsilon,2}$ that satisfy $E(\eta_t^i) = 0$ and $E(\varepsilon_t^i) = 0$ respectively.

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 $P9010$, $P9050$, $P5010$, the share of income growth higher than 50%, $P(\Delta^n y^i > 0.5)$, and lower than -50%, $P(\Delta^n y^i < -0.5)$, and the Crow-Siddiqui kurtosis of the earnings growth distribution of $n = 1, 3, 5$ between 1995-2000. We carry on the Simulated Method of Moments by giving equal weight to all the $n$-year differences.[32] Intuitively, higher differences ($n \geq 2$) identify permanent shocks, while the first difference identifies the transitory shock. Further details of the estimation method and the intuition for the identification can be found in Appendix C.2.

Table 12: Estimated Parameters

| Scenario | $p_\eta$ | $\mu_{\eta,1}$ | $\mu_{\eta,2}$ | $\sigma_{\eta,1}$ | $\sigma_{\eta,2}$ | $p_\varepsilon$ | $\mu_{\varepsilon,1}$ | $\mu_{\varepsilon,2}$ | $\sigma_{\varepsilon,1}$ | $\sigma_{\varepsilon,2}$ |
|---|---|---|---|---|---|---|---|---|---|---|
| pre-"China" | 0.1432 | 0.1994 | -0.0333 | 0.2083 | 0.1679 | 0.9327 | 0.1644 | -2.2777 | 0.1587 | 0.4015 |
| | (0.0262) | (0.0354) | . | (0.0308) | (0.0083) | (0.0174) | (0.0045) | . | (0.0318) | (0.1330) |
| Counterfactual | 0.1343 | 0.168 | -0.0261 | 0.2268 | 0.1944 | 0.9452 | 0.1471 | -2.5359 | 0.1772 | 0.4119 |
| | (0.0468) | (0.0633) | . | (0.0571) | (0.0154) | (0.0238) | (0.0105) | . | (0.0445) | (0.1092) |

*Notes:* Estimated parameters of the income process under different set of target moments. In the pre-"China" scenario, we target $P9010$, $P9050$, $P5010$, $P(\Delta^n y^i > 0.5)$, $P(\Delta^n y^i < -0.5)$, and the Crow-Siddiqui kurtosis of the earnings growth distribution of $n = 1, 3, 5$ between 1995-2000. In the counterfactual scenario, we target the same moments plus the counterfactual increase implied by their respective estimated coefficients and the weighted average increase of $\Delta IS_{rt}$ and $\Delta XD_{rt}$ from 2000 to 2015. Bootstrap standard errors in parenthesis (300 replications).

Table 12 and 13 present the estimated parameters and the implied moments of the mixtures used in the pre-China and the post-China counterfactual stochastic processes. The implied moments of the mixtures are in line with the distributions of Figure 1. The permanent component is closer to normality with relatively low variance, while the transitory component follows an asymmetric and leptokurtic distribution. Interestingly, the transitory component, with low probability, draws a shock from a distribution with a large negative mean. Since we did not explicitly model nonemployment shocks, we believe this distribution is partially picking up this effect.[33] In line with the results in section 5, the variance of both

[32]By construction, for every statistic from 1995 to 2000, there are five moments from the 1-year income changes distribution while only one from the 5-year distribution. We re-weight such that the contribution of the first-differences moments is exactly the same as the third and fifth-differences.

[33]This is in contrast with Guvenen et al. (2019), who found a large negative shock in the persistent mixture.

Table 13: Implied Moments of the Stochastic Processes

| | pre-China | | Counterfactual | |
|---|---|---|---|---|
| | Permanent ($\eta$) | Transitory ($\varepsilon$) | Permanent ($\eta$) | Transitory ($\varepsilon$) |
| Variance | 0.037 | 0.408 | 0.044 | 0.411 |
| Skewness | 0.337 | -3.267 | 0.167 | -3.588 |
| Kurtosis | 3.446 | 12.935 | 3.194 | 15.548 |

*Notes:* Implied variance, skewness and kurtosis of the permanent ($\eta$) and transitory mixture ($\varepsilon$) for the income process pre-"China" and counterfactual.

the permanent and the transitory components increased in the post-China counterfactual income process, while the skewness decreased.

## 7.2 The Model

To evaluate how much idiosyncratic shocks pass through consumption, we use a partial-equilibrium, life-cycle, incomplete-markets model in the line of Kaplan and Violante (2010) and De Nardi et al. (2020). The model is calibrated to approximate some of the features of the Brazilian economy.[34]

**Environment.** The model economy is characterized by a continuum of agents indexed by $i$. An individual is born and works until age $T_w$, when they enter the retirement period. At age $T$, the individual dies with certainty. Then, the expected lifetime utility of an agent is given by:

$$V = \mathbb{E}_0 \sum_{t=1}^{T} \beta^{t-1} u(c_t^i). \tag{14}$$

During the working period, workers earn gross labor income $w_t^i$, which is a function of a deterministic age-profile $\kappa_t$, and the stochastic term $y_t^i$, defined in equation (10):

$$\log w_t^i = \kappa_t + y_t^i. \tag{15}$$

We attribute these differences to our sample of highly attached workers, in which a large negative income shock (nonemployment) is usually followed by a large positive income shock (re-employment) in the following year.

[34]Nevertheless, we abstract from several features such as mortality risk, initial wealth distribution, bequests, means-tested programs, etc. Although a full calibration and welfare analysis of the Brazilian economy is interesting per se, it is out of the scope of this paper.

The gross labor income is translated to net labor income, $\tilde{w}_t^i$, using a function designed to mimic the Brazilian tax system $\tilde{w}_t^i = G(w_t^i)$.[35] Retired individuals receive a pension $p^i$ until they die. The pension is a function of the last earnings realization, $p^i = P(w_{T_w}^i)$.

Agents can invest in a risk-free asset, $a_t^i$, that pays a fixed rate of return $r$, but are only allowed to borrow up to an exogenous borrowing limit $\underline{a}$. They are born with no wealth. The agents' budget constraint is defined as:

$$\begin{aligned} c_t^i + a_{t+1}^i &= (1+r)a_t^i + \tilde{w}_t^i \qquad \text{if } t \leq T_w \\ c_t^i + a_{t+1}^i &= (1+r)a_t^i + p^i \qquad \text{if } t > T_w. \end{aligned} \tag{16}$$

**Calibration.** The model period is one year. Individuals enter the labor market at age 25, retire at age 55 ($T_w = 30$) and die at age 75 ($T = 50$). The per-period utility is a CRRA with the coefficient of relative risk aversion set to 2. We set the risk-free rate to 4% and the discount factor $\beta$ to match a wealth-to-income ratio of 2.5. The agents are not allowed to borrow, i.e. $\underline{a} = 0$.

The pension benefit is bounded by a maximum and a minimum value. Between these values, a retired worker is entitled to a replacement rate of 60% of her last earnings realization. The income process $y_t^i$ is estimated as described in Section 7.1.[36] The deterministic age profile, $\kappa_t$, is estimated using a full set of dummies and the same national sample from 1995-2000.[37] Finally, we introduce initial heterogeneity in labor income $\sigma_{z0}$ and calibrate it to match the cross-sectional variance of gross labor income at age 25.

**Welfare.** We assess the welfare cost of the increase in risk by calculating the consumption equivalent variation (CEV) that makes an unborn agent indifferent between living in the Brazil pre-China shock and the *riskier* post-China one. Intuitively, this would be equivalent to asking the agent how much consumption and contingencies (in percentage) she is willing to forgo in all future periods to be free of a riskier labor market. Note that this value measures only the cost coming from the increase in labor income risk, abstracting from changes in wage levels and other channels.[38]

Table 14 shows the results. We first report the CEV that makes the household indifferent between living in the riskier world (pre-China) and in one without uncertainty. A newborn

[35] The function replicates the statutory bracket values of the income tax and social security contribution in Brazil in 2000. It fully described in Appendix D.

[36] The income process is discretized using the simulation method outlined in De Nardi et al. (2020). The persistent component is discretized in 30 bins, while the transitory component is discretized in 8 bins.

[37] Since there is no time-variation in the model, we use the income at 2000 as the level value.

[38] We keep all other parameters constant, including the discount factor, which is calibrated using the pre-China stochastic process.

individual is willing to give 34.2% of consumption to be in a world without uncertainty, i.e. a world where her earnings follow a deterministic profile over the life cycle. In comparison, De Nardi et al. (2020) found that the consumption equivalent welfare cost of income risk in the U.S is equal to 26.2%.[39] Moreover, the welfare cost of the nonnormality is large. Rather than specify a mixture, we let the permanent and transitory component to be log-normal (where skewness is zero and kurtosis is 3), but with the same variances as before (as in Table 13). Relative to the baseline value, the welfare cost of earnings risk is 1.4 percentage points lower, about 32.8%.

Table 14: Welfare Cost of Labor Income Risk

| *Welfare Cost Relative to a World with no Uncertainty* | |
|---|---|
| pre-China | -34.22% |
| pre-China (log-normal process) | -32.83% |
| *Welfare Cost Relative to pre-China* | |
| Counterfactual | -4.42% |
| Counterfactual (log-normal process) | -2.11% |

Then, we show that a newborn agent is willing to trade 4.4% of his consumption to live a labor market less risky (pre-China levels), instead of facing the increase in risk following the trade shock. Again, results show that is important to account for nonnormality. If we perform the same exercise using a log-normal process with exclusively an increase in the variance (not accounting for changes in the higher-order moments), the computed CEV is 2.1%. Hence, ignoring the nonnormality substantially underestimates the welfare costs of the increase in income risk caused by the trade shock.

Finally, the analysis was carried on implicitly assuming that the increase in income risk is perpetual and abstract to any transitional dynamics. We acknowledge that part of the effect might be temporary 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.

[39] On top of doing their analysis for a different country, there are two reasons for the lower welfare cost: (i) they use disposable household earnings, while we use individual earnings, which is more volatile; (ii) in addition to nonnormality, their stochastic process also features nonlinearities and age-dependence. They show that age-dependence of the second moment reduces the welfare costs of earnings risk by 4 percentage points.

# 8 Conclusion

This paper studies the link between trade shocks and asymmetrical labor income risk. The heterogeneity of the Brazilian local labor markets combined with the rise of China in international trade provides an ideal natural experiment to understand the effect of an increase in import penetration on the degree of risk faced by workers. Moreover, the availability of high-frequency data containing longitudinal information on the universe of formally employed individuals in Brazil allows the construction of region-specific distributions of $n$-year income growth for each of the country's 509 local labor markets. This unique combination of factors is exactly what enables the study of the impact of trade on idiosyncratic earnings changes with a particular focus on the higher-order moments of the distribution.

We find that an increase in import penetration leads to a rise in the dispersion of the distribution of idiosyncratic income growth. The effect is concentrated in the lower tail, and grows larger as the lags between periods increase, suggesting a rise in the permanent risk. In the case of asymmetry, higher exposure to the trade shock leads to a disproportionate increase in the fraction of workers receiving large negative shocks, and to a more negatively skewed distribution. We show, then, that the impact of import penetration on the variance of idiosyncratic earnings growth can be largely explained by the increase in the volatility of hours worked annually, with a smaller effect on hourly wages. Additionally, the increase in dispersion comes both from a rise in the proportion of job and industry switchers, and from an increase in the volatility of the distribution of switchers. Similarly, the impact on the tails of the income distribution can also be explained by an increase in the fraction of switchers who experience large earnings changes.

Finally, 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. Afterward, we input the estimated parameters in an off-the-shelf incomplete markets model and compute the welfare cost implied by the increase in labor income risk. We find that a newborn worker is willing to forgo up to 4.4% of consumption to avoid the riskier labor market. Importantly, we show that, if we do not account for the nonnormality in the distribution of income growth, we would underestimate the welfare effect.

This paper is the first to exploit the regional distribution of an trade shock to investigate the impact of import penetration on earnings risk. Although the shift-share instruments combining a national aggregate shock with local compositions are standard in labor and trade applied papers, it had not yet been explored in the literature of income dynamics. We hope this could inspire future research that extends the current knowledge of the causal impact of aggregate economic shocks on earnings volatility. This is also the first paper to account for the higher moments of the distribution of income changes when studying the link between trade and risk. Yet, there are still some important aspects of this relationship that need to be explored further. For example, whether the changes in the distribution of income growth following the trade shock are permanent, or whether spillover effects on risk-sharing across regions occur are questions that remain unanswered and that are important avenues for future research.

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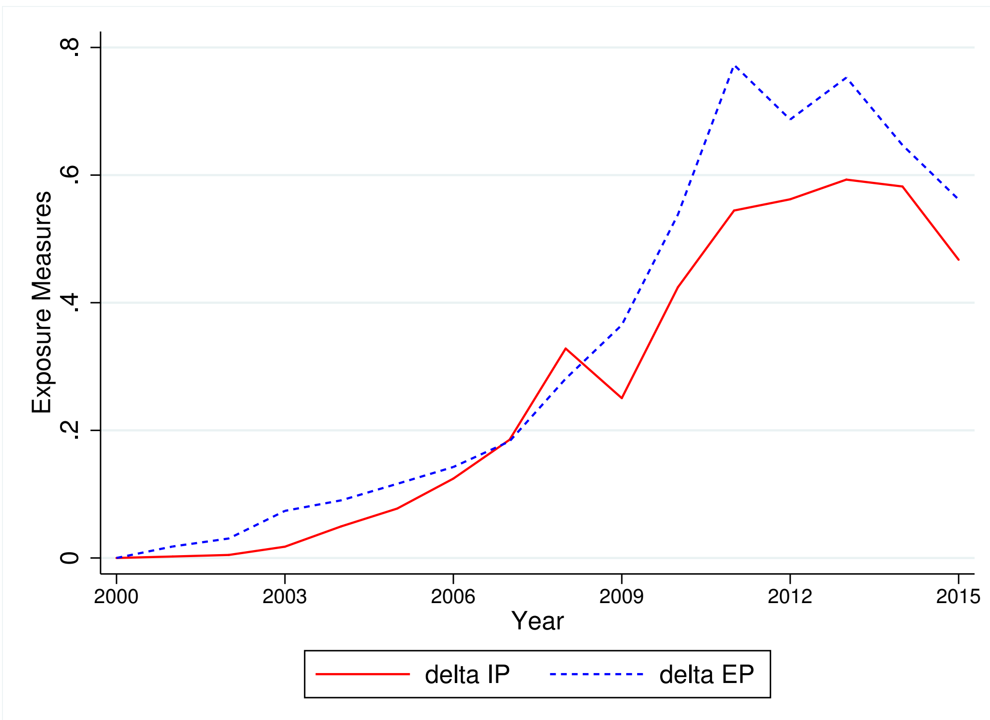
# Online Appendix

## Trade-induced Local Labor Market Shocks and Asymmetrical Labor Income Risk

**Tomás R. Martinez, Ursula Mello**

## A Additional Figures and Tables

Figure A.1: Average of $\Delta IP_{r\tau}$ and $\Delta EP_{r\tau}$ for $\tau = 2001, ..., 2015$




*Notes:* The figure plots the yearly average (population weighted) import ($\Delta IP_{r\tau}$) and export penetration ($\Delta EP_{r\tau}$) measures, for $\tau = 2001, ..., 2015$, as described in equations 5 and B.1.

Table A.1: Moments of Three-year Income Changes

| | | $m[\Delta^3 y^i_{r,2000}]$ | | |
|---|---|---|---|---|
| | Nat. | P25 | P50 | P75 |
| *Dispersion* | | | | |
| Variance | 0.535 | 0.480 | 0.545 | 0.597 |
| P9010 | 1.410 | 1.312 | 1.403 | 1.513 |
| *Asymmetry and Tails* | | | | |
| Skewness (Kelley) | 0.032 | -0.002 | 0.043 | 0.127 |
| $P(\Delta^n y^i_t < 0.0)$ | 0.462 | 0.449 | 0.467 | 0.508 |
| $P(\Delta^n y^i_t > 0.5)$ | 0.158 | 0.145 | 0.159 | 0.175 |
| $P(\Delta^n y^i_t < -0.5)$ | 0.127 | 0.115 | 0.126 | 0.139 |
| Kurtosis (C.S.) | 7.612 | 6.782 | 7.504 | 8.213 |

*Notes:* Values of $m_{r,2000}[\Delta^3 y^i]$. The skewness stands for the Kelley skewness, the kurtosis stands for the Crow-Siddiqui kurtosis and $P9010 = P90[\Delta^n y^i] - P10[\Delta^n y^i]$. The column Nat. present the moments for a national random sample of 400,000 workers. Columns P25, P50 and P75 denote the first, second, and third quartile moment value of 509 Brazilian local labor labor markets. Only moments calculated with more than 100 workers are used. Quartiles are weighted by the local labor labor workforce.

Table A.2: Brazil - China Trade Flows by Sector (Agriculture and Mining): 2000 and 2010

| Sector | Sector ID | Imports (2000) | Exports (2000) | Imports (2010) | Exports (2010) |
|---|---|---|---|---|---|
| agriculture - rice | 1101 | - | - | - | - |
| agriculture - maize | 1102 | - | - | - | 8,545.53 |
| agriculture - other cereals | 1103 | 12.56 | - | 893.79 | - |
| agriculture - cotton | 1104 | 2,729.93 | - | - | 151,775.88 |
| agriculture - sugar cane | 1105 | - | - | - | - |
| agriculture - tobacco | 1106 | 113.18 | 69,922.46 | - | 371,395.59 |
| agriculture - soya | 1107 | - | 469,505.47 | - | 7,722,001.91 |
| agriculture - manioc | 1108 | - | - | - | - |
| agriculture - flowers and ornamentals | 1111 | 21.07 | - | 21.30 | 99.55 |
| agriculture - citrus fruits | 1112 | - | 25.02 | - | 7.38 |
| agriculture - coffee | 1113 | - | 285.49 | - | 3,127.01 |
| agriculture - cocoa | 1114 | - | - | - | - |
| agriculture - grapes | 1115 | - | - | - | - |
| agriculture - bananas | 1116 | - | - | - | - |
| agriculture - other | 1117 | 10,628.95 | 577.67 | 202,520.23 | 1,778.34 |
| agriculture - bovine animals | 1201 | - | - | - | - |
| agriculture - sheep | 1203 | - | - | - | - |
| agriculture - pigs | 1204 | - | - | - | - |
| agriculture - birds | 1205 | - | - | - | - |
| agriculture - beekeeping | 1206 | - | 55.76 | 11.88 | 567.63 |
| agriculture - silk | 1207 | - | - | 810.26 | - |
| agriculture - other animals | 1208 | 497.30 | - | 14.03 | 1,384.82 |
| forestry | 2000 | 619.39 | 288.66 | 5,117.32 | 9,305.78 |
| fishing and aquaculture | 5000 | - | 12.65 | - | 81.14 |
| mining - coal | 10000 | 20,356.88 | - | 7,600.45 | 1.91 |
| mining - oil and gas | 11000 | - | 50,247.56 | - | 4,384,441.45 |
| mining - radioactive metals | 12000 | - | - | - | - |
| mining - precious metals | 13001 | - | - | - | - |
| mining - other metals | 13002 | 5,014.18 | 383,371.50 | 4,607.37 | 14,758,139.42 |
| mining - nonmetals for construction | 14001 | 907.09 | 14,597.11 | 3,185.21 | 31,400.78 |
| mining - precious stones | 14002 | - | 2,132.55 | 11.55 | 9,264.18 |
| mining - other nonmetals | 14003 | 1,225.26 | 1,702.86 | 11,514.72 | 1,747.60 |

**Notes:** Trade flows between Brazil and China in 2000 and 2010. Imports denotes Brazilian imports from China. Exports denotes Brazilian exports to China. Values in Thousands of 2014 US Dollars. Source: BACI-CEPII.

Table A.3: Brazil - China Trade Flows by Sector (Manufacturing): 2000 and 2010

| Sector | Sector ID | Imports (2000) | Exports (2000) | Imports (2010) | Exports (2010) |
|---|---|---|---|---|---|
| manuf - meat and fish | 15010 | 516.58 | 21,584.81 | 127,912.16 | 258,705.11 |
| manuf - fruits and vegetables | 15021 | 4,044.84 | 3,709.03 | 70,987.52 | 112,549.06 |
| manuf - oils and fats | 15022 | 26.60 | 48,663.75 | 337.71 | 863,099.42 |
| manuf - dairy products | 15030 | - | 38.29 | 730.12 | 3.14 |
| manuf - sugar | 15041 | 5.06 | - | 71.01 | 556,737.62 |
| manuf - coffee | 15042 | - | 467.08 | 13.66 | 1,552.38 |
| manuf - other food | 15043 | 3,983.85 | 1,870.68 | 79,979.36 | 16,068.36 |
| manuf - beverages | 15050 | 35.73 | 58.56 | 1,240.98 | 303.26 |
| manuf - tobacco | 16000 | 5.35 | - | - | - |
| manuf - spinning and weaving | 17001 | 27,240.81 | 955.99 | 779,107.85 | 11,618.68 |
| manuf - other textile products | 17002 | 23,071.86 | 209.88 | 856,177.72 | 5,181.85 |
| manuf - apparel | 18000 | 91,324.67 | 49.16 | 738,560.44 | 2,875.34 |
| manuf - leather processing | 19011 | 1,877.49 | 34,253.83 | 2,272.85 | 382,498.77 |
| manuf - leather products | 19012 | 1,881.12 | 64.51 | 21,749.57 | 34.80 |
| manuf - footwear | 19020 | 23,130.73 | 564.98 | 111,917.72 | 4,617.88 |
| manuf - wood products | 20000 | 4,403.34 | 47,387.88 | 31,499.45 | 80,461.96 |
| manuf - pulp and paper | 21001 | 176.77 | 95,933.65 | 95,436.58 | 1,328,157.79 |
| manuf - paper products | 21002 | 579.10 | 1,106.21 | 23,209.05 | 150.51 |
| manuf - printing and recording | 22000 | 3,396.72 | 18.09 | 67,709.80 | 140.19 |
| manuf - coke | 23010 | 77,506.29 | - | 216,396.99 | - |
| manuf - refined petroleum | 23020 | 224.67 | 31.44 | 63,562.67 | 465.96 |
| manuf - nuclear fuel | 23030 | - | - | - | - |
| manuf - paints and varnishes | 24010 | 623.54 | 216.91 | 8,160.95 | 4,059.11 |
| manuf - pharmaceuticals | 24020 | 65,688.88 | 7,225.35 | 533,589.69 | 33,031.93 |
| manuf - cleaning and hygiene products | 24030 | 155.04 | 82.07 | 26,357.06 | 26,529.15 |
| manuf - other chemicals | 24090 | 200,255.31 | 79,814.97 | 1,897,476.41 | 345,262.48 |
| manuf - rubber products | 25010 | 21,371.00 | 1,007.80 | 384,897.67 | 14,075.03 |
| manuf - plastic products | 25020 | 50,204.55 | 8,471.30 | 767,639.78 | 8,021.81 |
| manuf - glass products | 26010 | 16,916.41 | 2,139.90 | 195,661.39 | 6,415.19 |
| manuf - ceramic products | 26091 | 6,304.61 | 159.19 | 262,773.28 | 503.38 |
| manuf - other nonmetallic mineral products | 26092 | 2,642.49 | 9,918.04 | 63,607.10 | 9,266.30 |
| manuf - basic metals | 27000 | 35,506.53 | 72,902.19 | 1,762,985.50 | 879,999.17 |
| manuf - metal products | 28000 | 43,551.08 | 2,072.39 | 841,387.23 | 24,187.10 |
| manuf - machinery | 29001 | 117,505.62 | 48,353.03 | 3,760,904.29 | 205,610.45 |
| manuf - domestic appliances | 29002 | 28,451.64 | 358.72 | 564,472.24 | 1,207.31 |
| manuf - computing | 30000 | 176,556.42 | 815.22 | 1,826,052.79 | 5,235.43 |
| manuf - electrical equipment | 31000 | 165,756.24 | 6,065.64 | 2,187,793.80 | 28,707.16 |
| manuf - electronics | 32000 | 275,226.96 | 14,672.79 | 4,627,929.64 | 54,468.66 |
| manuf - medical instruments | 33001 | 6,263.26 | 500.05 | 150,508.87 | 2,225.09 |
| manuf - measuring instruments | 33002 | 10,310.56 | 1,192.87 | 192,696.94 | 9,087.87 |
| manuf - optical equipment | 33004 | 66,389.52 | 4,169.92 | 1,175,796.48 | 12,863.18 |
| manuf - watches and clocks | 33005 | 12,754.03 | 15.76 | 51,154.16 | 1.68 |
| manuf - motor vehicles | 34001 | 43.01 | 3,781.38 | 262,523.33 | 319.57 |
| manuf - motor vehicle bodies and parts | 34002 | 5,325.95 | 14,082.84 | 325,229.45 | 74,280.31 |
| manuf - shipbuilding | 35010 | 263.78 | - | 102,701.03 | - |
| manuf - railway products | 35020 | 58.01 | - | 2,976.26 | 233.99 |
| manuf - aircraft | 35030 | - | 51,651.78 | 637.72 | 411,304.60 |
| manuf - other transport | 35090 | 18,322.80 | - | 299,874.58 | 400.77 |
| manuf - furniture | 36010 | 3,219.22 | 192.34 | 147,244.22 | 92.30 |
| manuf - other | 36090 | 127,230.82 | 752.19 | 811,223.68 | 19,037.10 |

*Notes:* Trade flows between Brazil and China in 2000 and 2010. Imports denotes Brazilian imports from China. Exports denotes Brazilian exports to China. Values in Thousands of 2014 US Dollars. Source: BACI-CEPII.

Table A.4: Robustness of $\Delta IP_{r\tau}$ with different values of $\tau$

| | Var | P9010 | Skewness | $P(\Delta^n y_t^i > 0.5)$ | $P(\Delta^n y_t^i < -0.5)$ |
|---|---|---|---|---|---|
| *Panel A: $\tau$ = 2010* | | | | | |
| | $m[\Delta^5 y_{r,2015}^i]$ | | | | |
| $\Delta IP_r$ | 0.0408*** | 0.0864*** | -0.0348** | 0.00601*** | 0.0104*** |
| | (0.00606) | (0.0148) | (0.0139) | (0.00187) | (0.00302) |
| | $m[\Delta^3 y_{r,2015}^i]$ | | | | |
| $\Delta IP_r$ | 0.0299*** | 0.0704*** | -0.0315** | 0.00467*** | 0.00827*** |
| | (0.00547) | (0.0163) | (0.0158) | (0.00173) | (0.00255) |
| | $m[\Delta^1 y_{r,2015}^i]$ | | | | |
| $\Delta IP_r$ | 0.0153*** | 0.0596*** | -0.0224 | 0.00351** | 0.00643*** |
| | (0.00501) | (0.0219) | (0.0140) | (0.00159) | (0.00220) |
| Observations | 503 | 503 | 503 | 503 | 503 |
| 1st Stage F-Stat | 122.06 | 122.59 | 121.29 | 120.58 | 129.02 |
| *Panel B: $\tau$ = 2012* | | | | | |
| | $m[\Delta^5 y_{r,2015}^i]$ | | | | |
| $\Delta IP_r$ | 0.0326*** | 0.0694*** | -0.0280** | 0.00485*** | 0.00828*** |
| | (0.00481) | (0.0117) | (0.0109) | (0.00150) | (0.00238) |
| | $m[\Delta^3 y_{r,2015}^i]$ | | | | |
| $\Delta IP_r$ | 0.0240*** | 0.0567*** | -0.0253** | 0.00377*** | 0.00663*** |
| | (0.00438) | (0.0130) | (0.0124) | (0.00139) | (0.00202) |
| | $m[\Delta^1 y_{r,2015}^i]$ | | | | |
| $\Delta IP_r$ | 0.0123*** | 0.0481*** | -0.0182 | 0.00281** | 0.00518*** |
| | (0.00397) | (0.0173) | (0.0112) | (0.00126) | (0.00174) |
| Observations | 503 | 503 | 503 | 503 | 503 |
| 1st Stage F-Stat | 137.69 | 137.95 | 137.77 | 136.57 | 141.62 |

*Notes:* Using the IV framework, this table tests the robustness of the $\Delta IP_{r\tau}$ measure. In baseline, we define 2015 as the final year of the China shock and set $\tau$ equal to 2015 in equation 5. Here, we test whether the results change if we set $\tau$ equal to 2010 (Panel A) or 2012 (Panel B), other possible values for the final year of the shock, as seen in Figure A.1. All columns contain the full set of region controls in 2000, a control for the respective moment in year 2000 ($m[\Delta^1 y_{r,2000}^i]$) and dummies for the five broad geographic regions, as in our preferred specification. Standard errors in parenthesis are clustered at the mesoregion-level (130 units). Regressions are weighted by the size of the local labor force in 2000. *** p<0.01, ** p<0.05, * p<0.1.

Table A.5: Robustness of results with $m[\Delta^5 y^i_{r,2000}]$ as a control instead of $m[\Delta^1 y^i_{r,2000}]$

| | Var | P9010 | P9050 | P5010 | Skewness | $P(\Delta^n y^i_t < 0.0)$ | $P(\Delta^n y^i_t > 0.5)$ | $P(\Delta^n y^i_t < -0.5)$ | Kurtosis |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | $m[\Delta^5 y^i_{r,2015}]$ | | | | |
| $\Delta IP_r$ | 0.0390*** | 0.0727*** | 0.0170* | 0.0597*** | -0.0324** | -0.0151 | 0.00560*** | 0.00907*** | -0.0149 |
| | (0.00680) | (0.0135) | (0.0102) | (0.0130) | (0.0143) | (0.0101) | (0.00197) | (0.00288) | (0.0984) |
| | | | | | $m[\Delta^3 y^i_{r,2015}]$ | | | | |
| $\Delta IP_r$ | 0.0292*** | 0.0547*** | 0.00986 | 0.0484*** | -0.0281* | -0.0134 | 0.00403** | 0.00731*** | -0.0800 |
| | (0.00573) | (0.0142) | (0.0110) | (0.0142) | (0.0160) | (0.00829) | (0.00186) | (0.00239) | (0.128) |
| | | | | | $m[\Delta^1 y^i_{r,2015}]$ | | | | |
| $\Delta IP_r$ | 0.0142*** | 0.0413** | 0.0141 | 0.0334** | -0.0211 | -0.00296 | 0.00308* | 0.00565*** | -0.0828 |
| | (0.00525) | (0.0208) | (0.00913) | (0.0146) | (0.0137) | (0.0169) | (0.00157) | (0.00216) | (0.320) |
| Observations | 503 | 503 | 503 | 503 | 503 | 503 | 503 | 503 | 503 |
| 1st Stage F-Stat | 297.93 | 298.22 | 298.79 | 296.53 | 295.89 | 298.92 | 300.01 | 300.26 | 298.34 |

*Notes:* Using the IV framework, this table tests the robustness of results with respect to control $m[\Delta^1 y^i_{r,2000}]$. In our baseline results, we include, as a regression control, the respective moment for the one-year income growth between 1999 and 2000, the baseline year. The inclusion of this variable aims to control for possible short-term pre-trends, as explained in Section 4. In this table, we include as a control $m[\Delta^5 y^i_{r,2000}]$, computed for the five-year income growth between 1995 and 2000 to test whether results are robust to pre-trends defined at a longer time-period. All columns contain the full set of region controls in 2000, a control for the respective moment in year 2000 ($m[\Delta^5 y^i_{r,2000}]$) and dummies for the five broad geographic regions, as in our preferred specification. Standard errors in parenthesis are clustered at the mesoregion-level (130 units). Regressions are weighted by the size of the local labor force in 2000. *** p<0.01, ** p<0.05, * p<0.1.

Table A.6: Effect of $\Delta IP_r$ on the Dispersion of the Distribution of Income Growth: Job and Industry Switchers and Stayers

| | P9010 | P9050 | P5010 | P9010 | P9050 | P5010 |
|---|---|---|---|---|---|---|
| | *Job Switchers* | | | *Industry Switchers* | | |
| | $m[\Delta^5 y^i_{r,2015}]$ | | | $m[\Delta^5 y^i_{r,2015}]$ | | |
| $\Delta IP_r$ | 0.0826*** | 0.0266** | 0.0616*** | 0.0646*** | 0.0217* | 0.0518*** |
| | (0.0204) | (0.0110) | (0.0169) | (0.0212) | (0.0130) | (0.0143) |
| | $m[\Delta^1 y^i_{r,2015}]$ | | | $m[\Delta^1 y^i_{r,2015}]$ | | |
| $\Delta IP_r$ | 0.0896*** | 0.0340*** | 0.0577*** | 0.0461*** | 0.0212*** | 0.0342** |
| | (0.0160) | (0.0102) | (0.0137) | (0.0133) | (0.00791) | (0.0134) |
| Observations | 491 | 491 | 491 | 474 | 474 | 474 |
| 1st Stage F-Stat | 287.56 | 273.55 | 300.75 | 281.31 | 275.44 | 296.32 |
| | *Job Stayers* | | | *Industry Stayers* | | |
| | $m[\Delta^5 y^i_{r,2015}]$ | | | $m[\Delta^5 y^i_{r,2015}]$ | | |
| $\Delta IP_r$ | 0.0162 | -0.0103 | 0.0247*** | 0.0114 | -0.00984 | 0.0161* |
| | (0.0156) | (0.0135) | (0.00700) | (0.0141) | (0.0103) | (0.00889) |
| | $m[\Delta^1 y^i_{r,2015}]$ | | | $m[\Delta^1 y^i_{r,2015}]$ | | |
| $\Delta IP_r$ | 0.0407** | 0.00466 | 0.0310** | 0.0418** | 0.00594 | 0.0293** |
| | (0.0180) | (0.00644) | (0.0140) | (0.0193) | (0.00749) | (0.0135) |
| Observations | 494 | 494 | 494 | 501 | 501 | 501 |
| 1st Stage F-Stat | 291.92 | 294.75 | 290.92 | 292.50 | 300.31 | 294.49 |
| Region Controls in 2000 | Yes | Yes | Yes | Yes | Yes | Yes |
| $m[\Delta^1 y^i_{r,2000}]$ | Yes | Yes | Yes | Yes | Yes | Yes |
| Geographic Area FE | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes:* Using the IV framework, this table estimates the impact of import penetration $\Delta IP_r$ on the dispersion (P9010, P9050, and P5010) of five ($\Delta^5 y^i_{r,2015}$), and one-year ($\Delta^1 y^i_{r,2015}$) income growth of job and industry switchers, and job and industry stayers. Income growth is calculated between 2015 and 2015 - $n$, where $n = 5$ and 1. Region Controls in 2000 include: workers employed in the formal sector, the share of workers with high school and less of high school education, the size of the local workforce, the share of workers employed in informal jobs, the proportion of rural residents, the share of each region's workforce employed in agricultural, extractive and manufacturing sectors and a cubic polynomial of income per capita. The control $m[\Delta^1 y^i_{r,2000}]$ is the baseline value of the one-year income growth respective moment. The five Brazilian Macro-regions are North, Northeast, Central-West, Southeast and South. Standard errors in parenthesis are clustered at the mesoregion-level (130 units). Regressions are weighted by the share of the local labor force in 2000. Only regions with at least 100 individuals used to compute the moments are included. *** p<0.01, ** p<0.05, * p<0.1.

Table A.7: Effect of Trade Shock on Variance of Wages, Hours and Covariance between Wage and Hours for Five and One-year Growth Distributions: Job and Industry Switchers versus Stayers

| | *Job Switchers* | | | *Ind. Switchers* | | |
|---|---|---|---|---|---|---|
| | $V[\Delta^5 w^i_{r,2015}]$ | $V[\Delta^5 h^i_{r,2015}]$ | $C[\Delta^5 w^i_{r,2015}, \Delta^5 h^i_{r,2015}]$ | $V[\Delta^5 w^i_{r,2015}]$ | $V[\Delta^5 h^i_{r,2015}]$ | $C[\Delta^5 w^i_{r,2015}, \Delta^5 h^i_{r,2015}]$ |
| $\Delta IP_r$ | 0.0110** | 0.0289*** | 0.00864 | 0.00731 | 0.0181** | 0.0108 |
| | (0.00427) | (0.00710) | (0.00584) | (0.00610) | (0.00901) | (0.00668) |
| | $V[\Delta^1 w^i_{r,2015}]$ | $V[\Delta^1 h^i_{r,2015}]$ | $C[\Delta^1 w^i_{r,2015}, \Delta^1 h^i_{r,2015}]$ | $V[\Delta^1 w^i_{r,2015}]$ | $V[\Delta^1 h^i_{r,2015}]$ | $C[\Delta^1 w^i_{r,2015}, \Delta^1 h^i_{r,2015}]$ |
| $\Delta IP_r$ | 0.00736** | 0.0364*** | 0.00438* | 0.00363 | 0.0221*** | 0.00489 |
| | (0.00321) | (0.00774) | (0.00223) | (0.00416) | (0.00797) | (0.00312) |
| Observations | 491 | 491 | 491 | 474 | 474 | 474 |
| 1st Stage F-Stat | 290.21 | 290.17 | 300.56 | 285.67 | 285.24 | 297.70 |
| | *Job Stayers* | | | *Ind. Stayers* | | |
| | $V[\Delta^5 w^i_{r,2015}]$ | $V[\Delta^5 h^i_{r,2015}]$ | $C[\Delta^5 w^i_{r,2015}, \Delta^5 h^i_{r,2015}]$ | $V[\Delta^5 w^i_{r,2015}]$ | $V[\Delta^5 h^i_{r,2015}]$ | $C[\Delta^5 w^i_{r,2015}, \Delta^5 h^i_{r,2015}]$ |
| $\Delta IP_r$ | -0.00340 | 0.00120 | 0.00448 | -0.000699 | 0.000584 | 0.00133 |
| | (0.00798) | (0.00893) | (0.00744) | (0.00740) | (0.00865) | (0.00697) |
| | $V[\Delta^1 w^i_{r,2015}]$ | $V[\Delta^1 h^i_{r,2015}]$ | $C[\Delta^1 w^i_{r,2015}, \Delta^1 h^i_{r,2015}]$ | $V[\Delta^1 w^i_{r,2015}]$ | $V[\Delta^1 h^i_{r,2015}]$ | $C[\Delta^1 w^i_{r,2015}, \Delta^1 h^i_{r,2015}]$ |
| $\Delta IP_r$ | 0.00284 | 0.00666 | -1.54e-05 | 0.00233 | 0.00577 | 0.000170 |
| | (0.00239) | (0.00455) | (0.00231) | (0.00232) | (0.00486) | (0.00220) |
| Observations | 494 | 494 | 494 | 501 | 501 | 501 |
| Region Controls in 2000 | Yes | Yes | Yes | Yes | Yes | Yes |
| $V[\Delta^1 w^i_{r,2000}]$ | Yes | | | Yes | | |
| $V[\Delta^1 h^i_{r,2000}]$ | | Yes | | | Yes | |
| $COV[\Delta^1 w^i_{r,2000}, \Delta^1 h^i_{r,2000}]$ | | | Yes | | | Yes |
| Geographic Area FE | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes:* Using the IV framework, this table estimates the impact of import penetration $\Delta IP_r$ on the variance of five and one-year wages and hours growth, and on the covariance between the two, separately for switchers and stayers. The growth rate is calculated between 2015 and 2015 - $n$, where $n = 5$ and 1. Region Controls in 2000 include: workers employed in the formal sector, the share of workers with high school and less of high school education, the size of the local workforce, the share of workers employed in informal jobs, the proportion of rural residents, the share of each region's workforce employed in agricultural, extractive and manufacturing sectors and a cubic polynomial of income per capita. The control $V[\Delta^1 w^i_{r,2000}]//V[\Delta^1 h^i_{r,2000}]//COV[\Delta^1 w^i_{r,2000}, \Delta^1 h^i_{r,2000}]$ is the baseline value of the one-year growth for each outcome. The five Brazilian Macro-regions are North, Northeast, Central-West, Southeast and South. Standard errors in parenthesis are clustered at the mesoregion-level (130 units). Regressions are weighted by the share of the local labor force in 2000. *** p<0.01, ** p<0.05, * p<0.1.

# B Export Penetration

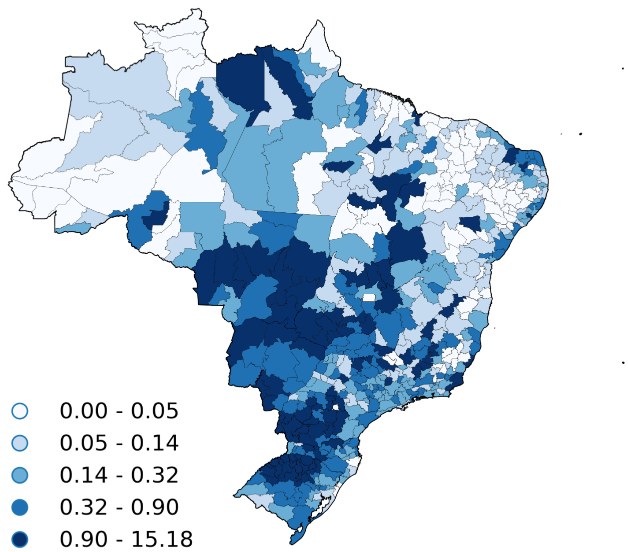
As discussed in Section 3.3, the *China rise* also caused positive export demand shocks in Brazil and in other commodities-based economies. Indeed, using data from the Brazilian Census containing formal and informal workers, Costa et al. (2016) found that the export demand shock induced by the Chinese surge between 2000 and 2010 led to an increase in growth rates of wages in the affected regions in Brazil. The effect of export penetration ($\Delta EP_r$) on income risk is, however, unclear. As explained in Section 3.3, a positive local labor market shock induced by trade could decrease income risk through an increase in wages and decrease in unemployment spells, but could also induce reallocation across sectors, leading to an increase in risk on the short run. Moreover, and most importantly, the export penatration shock is largely concentrated in the agricultural and extractive sectors, as shown in Panel C of Figure 2, which are disproportionately occupied by informal workers, who are, in turn, not covered in RAIS. Therefore, while in the main analysis of the paper we focus on the impact of import competition negative shocks, in this section, we exploit the effect of export penetration on income risk bearing in mind our data limitations.

We follow the same definition used in equation 5 for $\Delta IP_r$ and construct the variable for the export penetration (EP) shock in region r:

$$\Delta EP_r = \frac{1}{L_{r,2000}} \sum_j \frac{L_{rj,2000}}{L_{Bj,2000}} \Delta V_{BjC}. \tag{B.1}$$

The term $\Delta V_{BjC}$ denotes the change in the value of Brazil's exports to China between 2000 and year 2015. The terms $L_{r,2000}$, $L_{rj,2000}$ and $L_{Bj,2000}$ are defined as in equation 5. Figure B.1 shows the spatial distribution of $\Delta EP_r$ across Brazilian local labor markets. Differently than the $\Delta IP_r$ shown in Figure 3, which was mostly concentrated in the highly industrialized and most populated areas in the South and Southeast regions of Brazil, the $\Delta EP_r$ shock is more widespread across the Brazilian territory and mostly localized in the agricultural areas of the Center-west and the South and in smaller areas of the North and the Northeast. Importantly for our identification purposes, the raw correlation between the $\Delta IP_r$ and $\Delta EP_r$ variable is -6% (population weighted), although not statistically different from zero. Therefore, although the impact of the $\Delta EP_r$ shock on income risk is interesting *per se*, its absence from our main regressions should not bias our estimates.

Figure B.1: Distribution of changes in Export Penetration ($\Delta EP_r$)




*Notes:* The figure plots the distribution of variable $\Delta EP_r$ across Brazilian local labor markets. $\Delta EP_r$ measures changes in export penetration from 2000 to 2015, as defined by equation B.1. Values are measured in thousands of dollars per worker and plotted by quintiles.

Tables B.1, B.2 and B.3 Panel A present results of our regressions estimating the impact of $\Delta EP_r$, where we instrument $\Delta EP_r$ by $iv\Delta EP_r$, defined analogously to equation 8. In Panel B, then, we include $\Delta IP_r$ and $\Delta EP_r$ simultaneously. Table B.1 shows that the impact of $\Delta EP_r$ on the variance or the P9010 is close to zero and insignificant. This null impact, however, masks some heterogeneity. The export penetration shock leads to a small negative impact on the P9050 and a positive impact on the P5010. This is somewhat expected. As mentioned previously, the impact of export penetration on risk is ex-ante unclear, as it measures the overall combination of two factors: an increase in economic activity and reallocation across sectors. Finally, it is important to notice that the $\Delta IP_r$ shock increases risk in the bottom of the income distribution (P5010) and its effect is 7 to 8 times larger than the effect of $\Delta EP_r$.

Table B.2 shows that impact of $\Delta EP_r$ on assymetry and tails of the distribution is also small. An increase in $\Delta EP_r$ of \$1000 per worker reduces the share accounted by the P9050 in the P9010 distribution in 0.4, 0.7, and 0.9 p.p. for the five, three and one-year income growth distribution respectively. The analogous results for the $\Delta IP_r$ shock shown in Table B.2 were larger: 1.8, 1.7 and 1.2 p.p. Results for the $P(\Delta^n y_t^i < 0.0)$ show that an increase in $\Delta EP_r$ of \$1000 per worker decreases the probability of receiving a negative shock in income growth in 0.2, 0.5 and 1.2 p.p. for the five, three and one-year income growth distribution respectively. The results for $P(\Delta^n y_t^i > 0.5)$ and $P(\Delta^n y_t^i < -0.5)$ are close to zero and for the Kurtosis are not precisely estimated.

Finally, Table B.3 shows that the impact of $\Delta EP_r$ on the growth of labor income of hourly wages are close to zero and insignificant.

In sum, results from B.1, B.2 and B.3 show that, although the results induced by the $\Delta EP_r$ occur mostly in reasonable directions, they are expressively smaller in magnitude than the ones induced by the $\Delta IP_r$. Due to this empirical observation and to the fact that the economic literature mostly focuses on the impact of negative economic shocks on income risk, we focus our main analysis on the impact of $\Delta IP_r$. Importantly, however, we show that the existence of the $\Delta EP_r$ shock in Brazil does not affect our estimates for the coefficients of $\Delta IP_r$.

Table B.1: Effect of $\Delta EP_r$ on Dispersion of Income Growth

| *Panel A: Only Export Penetration* | | | | |
|---|---|---|---|---|
| | Variance | P9010 | P9050 | P5010 |
| | $m[\Delta^5 y^i_{r,2015}]$ | | | |
| $\Delta EP_r$ | 0.00205 | 0.00495 | -0.00423** | 0.00864*** |
| | (0.00168) | (0.00376) | (0.00204) | (0.00267) |
| | $m[\Delta^3 y^i_{r,2015}]$ | | | |
| $\Delta EP_r$ | 0.000861 | 0.00223 | -0.00848*** | 0.0104*** |
| | (0.00131) | (0.00284) | (0.00180) | (0.00274) |
| | $m[\Delta^1 y^i_{r,2015}]$ | | | |
| $\Delta EP_r$ | 0.000753 | 0.00368 | -0.00753*** | 0.0109*** |
| | (0.00124) | (0.00402) | (0.00238) | (0.00359) |
| Observations | 503 | 503 | 503 | 503 |
| 1st Stage F-Stat | 19.43 | 19.42 | 19.50 | 19.41 |
| *Panel B: Import and Export Penetration* | | | | |
| | Variance | P9010 | P9050 | P5010 |
| | $m[\Delta^5 y^i_{r,2015}]$ | | | |
| $\Delta IP_r$ | 0.0431*** | 0.0906*** | 0.0229** | 0.0672*** |
| | (0.00632) | (0.0146) | (0.00923) | (0.0124) |
| $\Delta EP_r$ | 0.000925 | 0.00266 | -0.00482** | 0.00686** |
| | (0.00192) | (0.00426) | (0.00219) | (0.00284) |
| | $m[\Delta^3 y^i_{r,2015}]$ | | | |
| $\Delta IP_r$ | 0.0324*** | 0.0735*** | 0.0173 | 0.0556*** |
| | (0.00559) | (0.0160) | (0.0105) | (0.0147) |
| $\Delta EP_r$ | 1.30e-05 | 0.000371 | -0.00893*** | 0.00894*** |
| | (0.00147) | (0.00310) | (0.00180) | (0.00279) |
| | $m[\Delta^1 y^i_{r,2015}]$ | | | |
| $\Delta IP_r$ | 0.0163*** | 0.0612*** | 0.0212** | 0.0391*** |
| | (0.00523) | (0.0223) | (0.00901) | (0.0147) |
| $\Delta EP_r$ | 0.000328 | 0.00213 | -0.00807*** | 0.00985*** |
| | (0.00133) | (0.00427) | (0.00245) | (0.00372) |
| Observations | 503 | 503 | 503 | 503 |
| 1st Stage F-Stat | 10.18 | 10.17 | 10.22 | 10.17 |

*Notes:* Using the IV framework, this table estimates the impact of export $\Delta EP_r$ and import penetration $\Delta IP_r$ on the dispersion of five ($\Delta^5 y^i_{r,2015}$), three ($\Delta^3 y^i_{r,2015}$) and one-year ($\Delta^1 y^i_{r,2015}$) income growth. Income growth is calculated between 2015 and 2015 - $n$, where $n = 5, 3$ and 1. All specifications include region controls in 2000 (workers employed in the formal sector, the share of workers with high school and less of high school education, the size of the local workforce, the share of workers employed in informal jobs, the proportion of rural residents, the share of each region's workforce employed in agricultural, extractive and manufacturing sectors and a cubic polynomial of income per capita), a control for the baseline value of the one-year income growth respective moment ($m[\Delta^1 y^i_{r,2000}]$) and dummies for the five Brazilian Macro-regions. Standard errors in parenthesis are clustered at the mesoregion-level (130 units). Regressions are weighted by the share of the local labor force in 2000. *** p<0.01, ** p<0.05, * p<0.1.

Table B.2: Effect of $\Delta EP_r$ on Asymmetry and Tails of Income Growth

| Panel A: Only Export Penetration | | | | | |
|---|---|---|---|---|---|
| | Skewness | $P(\Delta^n y_t^i < 0.0)$ | $P(\Delta^n y_t^i > 0.5)$ | $P(\Delta^n y_t^i < -0.5)$ | Kurtosis |
| | | | $m[\Delta^5 y^i_{r,2015}]$ | | |
| $\Delta EP_r$ | -0.00795*** | -0.00202* | -0.000187 | 0.000870 | 0.00615 |
| | (0.00206) | (0.00110) | (0.000399) | (0.000622) | (0.0155) |
| | | | $m[\Delta^3 y^i_{r,2015}]$ | | |
| $\Delta EP_r$ | -0.0134*** | -0.00520*** | -0.000958*** | 0.000976** | -0.0147 |
| | (0.00277) | (0.00129) | (0.000348) | (0.000468) | (0.0268) |
| | | | $m[\Delta^1 y^i_{r,2015}]$ | | |
| $\Delta EP_r$ | -0.0183*** | -0.0117*** | -0.000945*** | 0.00107** | -0.0825 |
| | (0.00367) | (0.00270) | (0.000329) | (0.000478) | (0.0747) |
| Observations | 503 | 503 | 503 | 503 | 503 |
| 1st Stage F-Stat | 19.53 | 19.50 | 19.53 | 19.40 | 19.61 |

| Panel B: Import and Export Penetration | | | | | |
|---|---|---|---|---|---|
| | Skewness | $P(\Delta^n y_t^i < 0.0)$ | $P(\Delta^n y_t^i > 0.5)$ | $P(\Delta^n y_t^i < -0.5)$ | Kurtosis |
| | | | $m[\Delta^5 y^i_{r,2015}]$ | | |
| $\Delta IP_r$ | -0.0330** | -0.0131 | 0.00665*** | 0.00993*** | -0.0132 |
| | (0.0136) | (0.00972) | (0.00195) | (0.00316) | (0.121) |
| $\Delta EP_r$ | -0.00708*** | -0.00168 | -0.000354 | 0.000616 | 0.00648 |
| | (0.00193) | (0.00110) | (0.000423) | (0.000673) | (0.0159) |
| | | | $m[\Delta^3 y^i_{r,2015}]$ | | |
| $\Delta IP_r$ | -0.0284* | -0.0101 | 0.00524*** | 0.00793*** | -0.0897 |
| | (0.0160) | (0.00776) | (0.00180) | (0.00257) | (0.147) |
| $\Delta EP_r$ | -0.0127*** | -0.00494*** | -0.00109*** | 0.000773 | -0.0125 |
| | (0.00257) | (0.00127) | (0.000351) | (0.000489) | (0.0274) |
| | | | $m[\Delta^1 y^i_{r,2015}]$ | | |
| $\Delta IP_r$ | -0.0168 | 0.00460 | 0.00408** | 0.00603*** | -0.145 |
| | (0.0127) | (0.0153) | (0.00161) | (0.00226) | (0.346) |
| $\Delta EP_r$ | -0.0178*** | -0.0118*** | -0.00105*** | 0.000916* | -0.0789 |
| | (0.00368) | (0.00279) | (0.000338) | (0.000503) | (0.0754) |
| Observations | 503 | 503 | 503 | 503 | 503 |
| 1st Stage F-Stat | 10.23 | 10.23 | 10.21 | 10.17 | 10.29 |

*Notes:* Using the IV framework, this table estimates the impact of export $\Delta EP_r$ and import penetration $\Delta IP_r$ on the asymmetry and tails of the income growth distribution. Income growth is calculated between 2015 and 2015 - $n$, where $n = 5, 3$ and 1. Skewness refers to the Kelley skewness and kurtosis refers to Crow-Siddiqui kurtosis. All specifications include region controls in 2000 (workers employed in the formal sector, the share of workers with high school and less of high school education, the size of the local workforce, the share of workers employed in informal jobs, the proportion of rural residents, the share of each region's workforce employed in agricultural, extractive and manufacturing sectors and a cubic polynomial of income per capita), a control for the baseline value of the one-year income growth respective moment ($m[\Delta^1 y^i_{r,2000}]$) and dummies for the five Brazilian Macro-regions. Standard errors in parenthesis are clustered at the mesoregion-level (130 units). Regressions are weighted by the share of the local labor force in 2000. *** p<0.01, ** p<0.05, * p<0.1.

Table B.3: Effect of $\Delta EP_r$ on Mean of Log of Labor Income Growth and Log of Hourly Wages Growth

| *Panel A: Only Export Penetration* | | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | $\mu[\Delta^{15}y^i_{r,2015}]$ | $\mu[\Delta^{5}y^i_{r,2015}]$ | $\mu[\Delta^{15}w^i_{r,2015}]$ | $\mu[\Delta^{5}w^i_{r,2015}]$ |
| $\Delta EP_r$ | 0.00235 | -0.000709 | 0.00482 | 0.000187 |
| | (0.00495) | (0.00157) | (0.00459) | (0.00184) |
| Observations | 503 | 503 | 503 | 503 |
| 1st Stage F-Stat | 19.34 | 19.34 | 19.51 | 19.51 |

| *Panel B: Import and Export Penetration* | | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | $\mu[\Delta^{15}y^i_{r,2015}]$ | $\mu[\Delta^{5}y^i_{r,2015}]$ | $\mu[\Delta^{15}w^i_{r,2015}]$ | $\mu[\Delta^{5}w^i_{r,2015}]$ |
| $\Delta IP_r$ | -0.0401* | -0.0214*** | -0.0361** | -0.0210*** |
| | (0.0203) | (0.00665) | (0.0173) | (0.00504) |
| $\Delta EP_r$ | 0.00342 | -0.000135 | 0.00573 | 0.000718 |
| | (0.00494) | (0.00165) | (0.00454) | (0.00186) |
| Observations | 503 | 503 | 503 | 503 |
| 1st Stage F-Stat | 10.13 | 10.13 | 10.20 | 10.20 |

*Notes:* Using the IV framework, This table estimates the impact of export $\Delta EP_r$ and import penetration $\Delta IP_r$ on the mean of Labor Income $\mu[\Delta^n y^i_{r,t}]$ and Hourly Wages' Growth $\mu[\Delta^n w^i_{r,t}]$. Income growth is calculated between 2015 and 2015 - $n$. All specifications include region controls in 2000 (workers employed in the formal sector, the share of workers with high school and less of high school education, the size of the local workforce, the share of workers employed in informal jobs, the proportion of rural residents, the share of each region's workforce employed in agricultural, extractive and manufacturing sectors and a cubic polynomial of income per capita), a control for the baseline value of the one-year income growth respective moment ($m[\Delta^1 y^i_{r,2000}]$) and dummies for the five Brazilian Macro-regions. Standard errors in parenthesis are clustered at the mesoregion-level (130 units). Regressions are weighted by the share of the local labor force in 2000. *** p<0.01, ** p<0.05, * p<0.1.

# C Income Process

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

## C.1 Higher Moments of the Income Process

In this subsection, we show that the $n-$year distribution of earnings change is informative about the higher moments of the stochastic process. From the income process of Section 2 and assuming $\rho = 1$, we have:

$$\Delta^n y^i_{r,t} = \sum_{k=0}^{n-1} \eta^i_{r,t-k} + \varepsilon^i_{r,t} - \varepsilon^i_{r,t-n}. \tag{C.1}$$

Let us denote $k^j(x(t))$ as the $j_{th}$ cumulant of the of the distribution $F_x(t)$.[40] Then, applying the properties of the cumulants it is easy to see that:

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

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

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

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

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

[40] 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

We estimate two stochastic income processes. The first income process is estimated targeting empirical moments of the distribution of income growth using the nationwide sample of 400,000 individuals from 1995 to 2000 applying the same restrictions of the empirical data. The second income process is estimated targeting the counterfactual moments of income growth implied by the causal estimates. The counterfactual moments are constructed by summing the empirical moments used in the previous estimation plus the (weighted) average increase of $\Delta IS_r$ and $\Delta XD_r$ times the estimated coefficients of the previous sections. The nationwide moments of the distribution of one-year and five-year earnings growth are outlined in Table 2, while the moments of the three-year earnings growth are in Table A.1. The counterfactual moments are constructed by summing the moments of Tables 2 and A.1 with the the (weighted) average increase of $\Delta IS_{rt}$ (0.467) and $\Delta XD_{rt}$ (0.564) times the estimated coefficients taken from Tables 4 and 5 (effect of $\Delta IS_{rt}$), and Panel A of Tables B.1 and B.2 (effect of $\Delta XD_{rt}$).[41] The estimated income process is given by:

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

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

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

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

We 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 carry on the estimation using simulated method of moments. Particularly, we target the $P9010$, $P9050$, $P5010$, the share of income growth higher than 50%, $P(\Delta^n y_i > 0.5)$, and lower than -50%,$P(\Delta^n y_i < -0.5)$, and the Crow-Siddiqui kurtosis of the one, three, and five-year earnings growth distribution. We give equal weight for $P9010$, $P9050$, $P5010$, and the Crow-Siddiqui kurtosis (20% each), and 10% weight for the share of income growth higher than 50% and for the share of income growth lower than -50%. Moreover, for every statistic from 1995 to 2000, there are five moments from the one-year income growth distribution while only one from the five-year

[41] For example, the $P9010[\Delta^5 y^i_{2000}]$ is equal to 1.627. The post-China counterfactual P9010 is calculated as $P9010[\Delta^5 y^i_{CF}] = 1.627 + 0.467 \times 0.0915 + 0.562 \times 0.0049 = 1.67$, where 0.467 and 0.564 are the average increase of $\Delta IS_{rt}$ and $\Delta XD_{rt}$. In practice, most of the coefficients of $\Delta XD_{rt}$ are an order of magnitude smaller than the ones from $\Delta IS_{rt}$, and therefore are irrelevant for the estimation.

distribution. We re-weight such that the contribution of the first-differences moments is exactly the same as the third and fifth-differences (i.e. dividing the first-differences by five and the third-differences by three). We proceed by simulating 90,000 of income histories using equation C.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 $j$:

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

Finally, we stack all moments conditions: $F(\Theta) = [F_1(\Theta), F_2(\Theta), ..., F_J(\Theta)]'$ and minimize the loss function:

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

Where $W$, is the weighting matrix with the weights discussed above. 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 10000 initial parameter vectors (chosen based on a Sobol sequence). Afterward, based on the loss function, the 5% best guesses are selected and carried for the second stage of the 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 C.11. We compute standard errors using block bootstrap at the individual level (300 replications).

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 C.2. Obviously, since we are not targeting the central moments, the direct identification argument cannot be used. Nevertheless, the percentile-based moments provide similar information, hence, the intuition remains. Suppose that we have four observations such that: $t+1, t, t-1, t-2$. Notice that:

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

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

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.

# D Model

## D.1 Tax, Social Security contribution and Pension functions

In the data, labor income $w_t^i$ is measured before taxes and contributions. We translate gross to net labor income using a function $G(.)$: $\tilde{w}_t^i = G(w_t^i)$. The function aims to replicate the tax system in Brazil in 2000 and is defined as following:

1. We deduct social security contributions from gross yearly labor income and recover taxable income: $\hat{w}_t^i = w_t^i - \tau_{ss}(w_t^i)$, where $\tau_{ss}(w_t^i)$ follows the brackets:

$$\tau_{ss} = \begin{cases} 0.0765 \times w_t^i & \text{if } w_t^i \leq 4,895.80 \\ 0.0865 \times w_t^i & \text{if } 4,895.80 < w_t^i \leq 5,304.00 \\ 0.09 \times w_t^i & \text{if } 5,304.00 < w_t^i \leq 8,159.58 \\ 0.11 \times w_t^i & \text{if } 8,159.58 < w_t^i \leq 16,319.16 \\ 0.11 \times 16,319.16 & \text{if } 16,319.16 < w_t^i \end{cases} \tag{D.1}$$

2. Then, we apply the income tax on the taxable income and find net labor income $\tilde{w}_t^i = \hat{w}_t^i - \tau_{inc}(\hat{w}_t^i)$. The income tax follows the schedule:

$$\tau_{inc} = \begin{cases} 0.0 & \text{if } \hat{w}_t^i \leq 10,800.0 \\ 0.15 \times \hat{w}_t^i - 1620.0 & \text{if } 10,800.0 \leq \hat{w}_t^i \leq 21,600.0 \\ 0.275 \times \hat{w}_t^i - 4320.0 & \text{if } 21,600.0 < \hat{w}_t^i \end{cases} \tag{D.2}$$

The pension $p^i$ is a function of the last income realization $p^i = P(w_{T_w}^i)$. The pension yields a replacement rate of 60% of the individuals last realization bounded by a minimum and a maximum value:[42]

$$p^i = \begin{cases} 1,963.00 & \text{if } w_{T_w}^i \times 0.6 \leq 1,963.00 \\ w_{T_w}^i \times 0.6 & \text{if } 1,963.00 \leq w_{T_w}^i \times 0.6 \leq 17,267.25 \\ 17,267.25 & \text{if } 17,267.25 < w_{T_w}^i \times 0.6 \end{cases} \tag{D.3}$$

[42]According to the OCDE pension statistics, the replacement rate is equal to 69% for men and 52% for women in Brazil.