Trade Shocks and Higher-Order Earnings Risk in Local Labor Markets*

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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. We find that an increase in import penetration leads to a more dispersed and negatively skewed distribution. These effects can be explained by an increase in the volatility of hours worked following job and industry transitions, particularly from involuntary job separations. Moreover, the observed increase in the dispersion of the distribution across the years suggests a temporary rise in the persistent risk, stemming from the broad reallocation of labor following the trade shock. Through the lens of an incomplete market model, individuals would be willing to forgo as much as 1.8% of consumption to avoid the riskier labor market.

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 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; Busch et al., 2022). Despite their 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 impact earnings risk, finding that a rise in import competition, or a downward tariff change, increases its variance (Krishna and Senses, 2014; 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 to fill this gap. In light of the new advances in the income dynamics literature, we first investigate how local labor market shocks induced by trade impact 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. This involves investigating how trade shocks impact the earnings growth of job and industry switchers compared to those who remain in their jobs, changes in the distribution of hours worked versus hourly wages, and changes in earnings dispersion for individuals who experienced layoffs versus those who voluntarily left their jobs or had no job separations. 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 workers' heterogeneous characteristics. 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 a policy perspective. It is well known that, even keeping average wages constant, riskier labor markets can have pervasive consequences for individual welfare.[1] Previous evidence has shown that trade shocks might impact labor market volatility in two ways. First, it can induce reallocation of workers within and across industries, sometimes associated with long unemployment spells

[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.

and loss of human capital (Dix-Carneiro, 2014). As far as *ex-ante* similar 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 on 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 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 for 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 our sample based on a revolving panel following the standard methodology in the income dynamics literature. Given the recent focus on nonnormal income growth highlighted by Guvenen et al. (2021), our examination is not limited to the variance but also focuses on the asymmetry and tails of the distribution. It is precisely 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

[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) show that higher integration with global markets increases unemployment, wage inequality, and firm-level volatility.

somewhat untouched by it. Yet, as in much of the literature, the shift-share estimates would 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 (ΔIP_r) from China increase the dispersion of income growth as measured both by the variance and the P9010. Moreover, the impact of ΔIP_r on dispersion is larger for longer time differences and concentrated in the lower tail of the distribution. Turning to higher-order moments, we find that increased import penetration results in a more negatively skewed distribution of income growth, and increases the proportion of individuals experiencing substantial negative income shocks, with no notable effects on those receiving large positive shocks.

The surge in asymmetrical earnings risks can be attributed to several mechanisms, pointing to the role of the costly reallocation of labor following a trade shock. First, we find that the increase of workers switching industries could explain about half of the rise in the dispersion of earnings change in high import-penetration regions. Moreover, we find that the dispersion of earnings growth, particularly in the lower tail of the distribution, increases for individuals who change jobs and industries. Second, the increase in volatility in annual hours following the import penetration shock also points to the importance of nonemployment spells as a possible explanation for the asymmetrical earnings risk. For instance, we find that the rise in lower-tail risk is concentrated in workers who suffered layoffs, with no effects on the individuals who voluntarily leave their jobs or those who do not experience job separations. Lastly, separating our sample into different subgroups reinforces this narrative. Workers in both tradable and non-tradable industries experience an increase in the negative idiosyncratic income shocks, but only workers in tradable industries suffer a decline in positive shocks (i.e., right tail). This observation underscores the inability of the workers who suffer more from the China shock to transition out of tradable industries.

Since our empirical findings point towards the riskier reallocation of labor as a driver of labor income risk, it naturally raises the question of whether the risk profile will revert to normal once the transition dynamics following the trade shock fade out. The evidence we present indicates that, by the end of our sample period, the impact of the trade shock on the distribution of earnings growth diminishes, becoming almost indistinguishable between regions with high and low import penetration. It is worth noting that, even though the trade shock might be temporary, the *idiosyncratic shocks* can be very persistent, suggesting lasting consequences for the affected individuals.

Finally, we quantify the welfare cost caused by the increase in labor income risk from the China shock. Specifically, we estimate two income processes with higher-order moments for high and low-skill workers: 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. Using an incomplete market model, we find that the welfare costs can be as high as 1.8%. Importantly, under the assumption that the rise in earnings risk is temporary, we find that welfare losses are larger for young workers, highlighting the importance of self-insurance as a mechanism to buffer the increase in risk stemming from a trade shock.

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. (2021) 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; Sanchez and Wellschmied, 2020), and over the business cycles (Guvenen et al., 2014; McKay, 2017; Busch et al., 2022). 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 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

[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) and Engbom et al. (2022) have studied the earnings dynamics in and out of the formal and informal sector. Because of data limitations, they focus only on one-year earnings growth.

- on the distribution of earnings growth. Third, we contribute to the recent discussion of whether the nonnormality of earnings fluctuations is driven by changes in the distribution of wages or hours (Hoffmann and Malacrino, 2019; Halvorsen et al., 2023; 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).[6] 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 and the mechanisms behind the increased volatility.

Finally, we contribute to the vast literature that studies labor market adjustments following trade shocks.[7] 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 (Autor et al., 2013, 2014). In the case of Brazil, the "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 from 2000 to 2010, while the import supply shock is related to lower wage growth for manufacturing workers. In this paper, we show that the increase of *volatility of earnings* after a trade shock - a different dimension of the labor market experience -, and, in particular, its higher-moments, can be an important source of welfare

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

[6] 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 on the variance of the idiosyncratic risk.

[7] 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, 2019).

losses.[8]

2 Data and Descriptive Statistics

2.1 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 1991 to 2018. 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 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. As will become clear throughout the paper, the data allows us to observe employment as well as periods of nonemployment. One limitation of the data is that we only observe contractual hours per week (which are fixed during the employment spell), as opposed to actual hours worked, limiting the variation in annual hours to mainly the extensive margin of employment. This means, for instance, if an individual decides to work overtime, we observe the extra income but not the extra hours.

We construct our sample based on a revolving panel following the standard methodology in the income dynamics literature (Guvenen et al., 2021). For an individual to be in the sample in year t, (i) he or she must be between 25 and 55 years old, (ii) must have earnings above two months of the yearly minimum wage in $t-1$, and in at least once more in $t-2$, $t-3$ or $t-4$. Then, for each worker in our sample in year t, we compute the earnings growth between t and $t+n$ (net from age and year fixed effects, as defined below). In the rest of the paper, we refer to the average earnings between $t-1$ and $t-4$ as the worker's *permanent*

[8] It is important to note that the concept of labor market volatility (risk) aims to capture a dimension of the labor market experience that was not studied by these previous papers, which focus on the links between trade, wage levels, and wage inequality. As exemplified by Krishna and Senses (2014), while the distribution of incomes could stay the same between two time periods (i.e. with no change in inequality), workers could stochastically exchange positions with each other under the same income distribution, thus experiencing risk.

income. All the nominal earnings are deflated using the official price index (IPCA).

For most of the paper, we work with the distributions of annual earnings growth 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. Since our goal is to characterize the differences in 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.[9] Precisely, we define the residual-earnings growth of an individual i located initially in local labor market r between t and $t+n$ as $\Delta^n y^i_{r,t} \equiv y^i_{r_{t+n},t+n} - y^i_{r_t,t}$. Therefore, when referring to earnings growth, we are using *residual-earnings log changes*.[10] Note that we do not restrict the worker to be in the same local labor market in both periods.

Informality. Brazil has a large informal sector and previous evidence has shown that trade shocks might affect the degree of the informality of local markets (Costa et al., 2016; Dix-Carneiro and Kovak, 2019). Thus, the largest limitation of our data is that it only covers formal employers, making an unemployment spell indistinguishable from employment in the informal sector. To alleviate concerns that moves in and out of the formal sector would bias our estimates of earnings volatility in the microregion, our sample is restricted to individuals highly attached to the formal labor market. For instance, to compute a one-year earnings growth, the individual should be observed in the formal sector at least four times every six years (in t, $t+1$, and twice between $t-1$ and $t-4$). This aligns with the literature on income dynamics (Guvenen et al., 2021; Halvorsen et al., 2023). There is a clear trade-off with the restrictions we impose. On the one hand, by doing this, we minimize concerns that the selection in and out of the formal sector would bias our estimates of volatility. On the other hand, imposing a restriction of too many years of employment in the formal sector means that we ultimately study how trade impacts the volatility of workers highly attached to the formal sector resulting in the loss of important unemployment dynamics.

Moreover, it is in principle unclear whether the absence of the informal sector increases or decreases income volatility. On the one hand, the earnings of workers employed in the informal sector are more volatile than the ones in the formal sector. On the other hand, the

[9] An alternative specification is to include additional factors accounting for occupations, industries, or employers. We do not include these factors because we aim to capture the income changes produced by changes in the occupation/employer.

[10] We follow the large literature on income dynamics and use the log changes as a growth rate measure. Obviously, this measure ignores potentially valuable information on the extensive margin (i.e., the zeros). Given that our sample selection focuses on workers highly attached to the formal labor market, results are likely to remain robust to measures that incorporate zero earnings, such as arc-percent changes. Indeed, Guvenen et al. (2021) and Halvorsen et al. (2023) show very similar results when comparing both measures.

informal sector may act as a buffer after a job loss and hence may reduce earnings changes between two periods. Since there is no data representative at the local labor market level that makes it possible to follow workers employed in the informal sector, we assess the direction of our estimates by looking at studies that used surveys representative only at the national level (Gomes et al., 2020) or that only covers the largest metropolitan areas (Engbom et al., 2022). First, both studies point out that earnings in the informal sector are between 1.5 to 1.8 times more volatile than in the formal sector (in ratios of standard deviations of residual-earnings log change). Sector switchers experience an even larger earnings volatility. Second, individuals that transit from the formal to the informal sector experience large negative earnings growth, suggesting that the informal sector provides a limited capacity to buffer negative shocks in the formal sector. Finally, Engbom et al. (2022) finds that the probability that a worker stays in the formal sector for consecutive years far outweighs the probability of transitions from formality to informality. Moreover, they find that conditional on being in the formal sector, high-income workers have a lower probability of transitioning to the informal sector. Given that our sample is composed of high-income workers (relative to the universe of formal sector workers, see Table 1), it is likely that they also have a low probability of transitioning to informality. Taken together, these empirical facts suggest that our estimates likely provide a lower bound for the earnings volatility.

Summary Statistics. Our unit of analysis is the microregion as defined by the Brazilian statistical agency, a set of municipalities that are connected through a relation of dependence and displacement of the population in search of goods, services, and work. This definition is akin to the commuting zone often used in the U.S. We refer to them as regions or local labor markets interchangeably to avoid repetition. Our final sample adds up to around 484.6 million worker-year observations distributed over 24 years in 509 local labor markets.

Table 1 provides a comparison between our baseline sample from RAIS with the restrictions discussed above (column 1), all individuals 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 monthly income in 2000 in RAIS is given by 805 BRL, this value is 818 in the Census.[11] Furthermore, the demographics match quite closely. The share of men and the average age are, respectively, equal to 62% and 38 years old in RAIS and 58.5% and 38 years old in the Census. There are

[11] Notice that the annual labor income differs substantially between RAIS and the Census. The difference arises because, in RAIS, we consider the months worked per year. 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.

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	10212.68	8462.10	9819.42	8165.46	9373.24
Monthly labor income	927.09	805.30	818.29	680.45	781.10
Hours worked per week	40.8	41.1	43.8	43.7	44.5
Months worked per year	10.7	9.9	-	-	-
Average age	38.4	37.8	37.9	37.9	38.6
Share Male	63.3	62.5	58.5	57.2	61.9
Education Level					
Less than high school	61.1	64.1	57.3	65.0	67.1
High school	26.3	24.8	29.1	24.4	22.7
College	12.6	11.0	13.6	10.7	10.2
Sector					
Share agriculture	5.1	6.2	5.7	9.4	12.8
Share manufacturing	19.1	18.1	17.4	15.1	13.7
Non-tradable	75.8	75.7	76.9	75.5	73.6
Share formal workers	100.0	100.0	100.0	69.9	47.8

Notes: All columns include workers between 27-55 years old with positive labor income in 2000. Given that the Census monthly income is from the main job only, to make it comparable we exclude workers with multiple jobs in RAIS (about 2%). *Baseline* is all workers used in the main analysis. *All RAIS* is all workers in RAIS with only the age restriction. *Formal* includes paid workers in the Census who are formally employed. *Formal & Informal* adds informal paid workers. *All* includes additionally self-employed and entrepreneurs. Values in 2000 Brazilian Reals.

small differences across educational levels, which we attribute to how education is collected in the two datasets.[12]

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 0.8 more months per year. This is expected 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. An important characteristic of our baseline sample is its initial sectoral share. The agricultural/extractive sector is particularly under-represented in RAIS. Only 5.1% of the workers are located in industries from the agricultural/extractive

[12]In the Census, the number of years of education is reported directly by the worker, while 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 misreports. Hence, it is likely that many firms do not track the precise level of education of their employees and report an approximation.

sector, while in the full Census (column 5), around 12.8% 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 19.1% of the sample comprises workers in the manufacturing industries, almost six percentage points more than in the full sample from the Census.

2.2 Distributions of Labor Income Growth

As discussed before, the empirical objects of our analysis are the distributions of differences of annual log labor income net of age and year effects. We define the moment of the distribution of the residualized earnings growth in the local labor market r between t and $t+n$ as $m[\Delta^n y^i_{r,t}]$. Given the recent advances in the income dynamics literature highlighted by Guvenen et al. (2021) and others, our analysis has a special focus on the asymmetry and the tails of the income-changes distribution. In Appendix Figure A.1, we show that the distributions of one and five-year earnings growth in Brazil, similarly to the U.S., are asymmetrical and display a large mass of workers with little income change from one year to the other. Thus, assuming normality and focusing on second moments only would entail a great loss of information.

Table 2 presents selected moments of the distributions of one ($m[\Delta^1 y^i_{1999}]$) and five-year ($m[\Delta^5 y^i_{1995}]$) earnings growth in Brazil as a whole (Column *Nat.*) and in its local labor markets.[13] 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 regions. 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 the dispersion is larger for the 5^{th} lag of log income differences. Furthermore, regions in 75^{th} percentile are roughly 22% more disperse than the regions in the 25^{th} percentile for $Var[\Delta^1 y^i_{r,1999}]$ and 18% for $Var[\Delta^5 y^i_{r,1995}]$.

To measure the asymmetry, we rely on a quantile-based measure of skewness, the Kelley skewness:

$$\mathcal{S}_k = \frac{(P90 - P50) - (P50 - P10)}{(P90 - P10)}. \tag{1}$$

[13] Table A.1 presents the same moments for the distribution of three-year earnings growth ($m[\Delta^3 y^i_{1997}]$).

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

	$m[\Delta^1 y^i_{1999}]$	$m[\Delta^1 y^i_{r,1999}]$			$m[\Delta^5 y^i_{1995}]$	$m[\Delta^5 y^i_{r,1995}]$		
	Nat.	P25	P50	P75	Nat.	P25	P50	P75
Dispersion								
Variance	0.322	0.281	0.314	0.342	0.601	0.544	0.625	0.644
P9010	0.897	0.799	0.895	0.994	1.570	1.466	1.587	1.665
P9050	0.414	0.347	0.378	0.427	0.698	0.644	0.676	0.723
P5010	0.482	0.422	0.501	0.579	0.872	0.813	0.902	0.961
Asymmetry and Tails								
Kelley Skewness	-0.076	-0.186	-0.093	-0.056	-0.111	-0.170	-0.135	-0.087
$P(\Delta^n y^i_t > 0.5)$	0.078	0.070	0.073	0.083	0.170	0.147	0.173	0.202
$P(\Delta^n y^i_t < -0.5)$	0.102	0.091	0.102	0.115	0.161	0.136	0.169	0.179
C.S. Kurtosis	12.533	12.188	13.880	15.149	5.717	5.304	5.844	6.139

Notes: Values of $m[\Delta^1 y^i_{r,1999}]$ and $m[\Delta^5 y^i_{r,1995}]$. C.S 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 all workers. Columns P25, P50, and P75 denote the first, second, and third quartile moment values of 509 Brazilian local labor markets. Quartiles are weighted by the local 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 for by the upper tail of the distribution. Table 2 shows that the upper tail explains 46% of the dispersion of $\Delta^1 y^i_{1999}$ and 44% of $\Delta^5 y^i_{1995}$. Again, there is substantial variation in the asymmetry across regions.

To examine the tails of the distribution, we use three 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 Appendix Figure A.1, the kurtosis is substantially higher for $\Delta^1 y^i_{1999}$ than for $\Delta^5 y^i_{1995}$. 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 log changes larger than 0.5, $P(\Delta^n y^i_t > 0.5)$, and the share of log changes smaller than -0.5, $P(\Delta^n y_t^i < -0.5)$, are larger for $\Delta^5 y_{1995}^i$ than for $\Delta^1 y_{1999}^i$. Finally, in Appendix Table A.2, we show all the average moments grouping local labor markets by variance quintile. We observe that local labor markets with higher variance have a more negative Kelley skewness and a lower Crow-Siddiqui kurtosis.

2.3 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) data available at RAIS.[14] We create a mapping between the two that results in 82 traded sectors, including 22 agricultural, 10 extractive, and 50 manufacturing sectors (Tables A.3 and A.4, in the Appendix).

Since the trading 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.

As carefully described in Autor et al. (2016), there are some features of the *China rise* that make it particularly interesting for the study of the causal effects of trade: its unexpected nature, the substantial opportunity for catching up due to the country's high degree of isolation, and China's comparative advantages, which created trade shocks of a specific pattern that differently affected countries and local labor markets, according to their previous sectoral specialization. Figure A.2 Panel B shows the Chinese comparative advantage in the production of manufacturing goods when compared to agricultural or extractive products. Although the Chinese trade expansion started in the early 1990s, it accelerated substantially in the 2000s (Figure A.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.

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 special-

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

ization affected the Brazilian economy in a particular way. In Figure A.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 the understanding of the relationship between trade and income risk.[15] We thus focus the main analysis on the impact of import-competition shocks in the formal sector. To do so, we define the following measure for import penetration at the local labor market level:

$$\Delta IP_{r\tau} = \sum_j \frac{L_{rj,2000}}{L_{Bj,2000}} \frac{\Delta V_{CjB,\tau}}{L_{r,2000}} \tag{2}$$

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 τ 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 τ from now on.[16] 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 ΔIP_r is

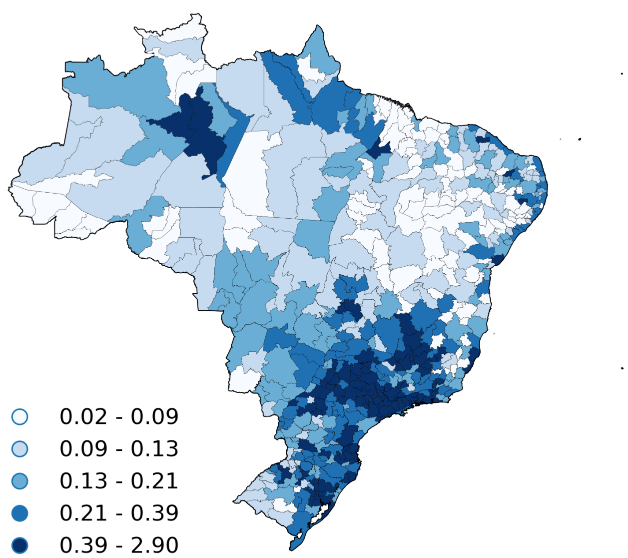
[15]This is so for two reasons. First, a large body of the literature has documented that idiosyncratic earnings risk is highly persistent and countercyclical (Storesletten et al. (2004a) and Hoffmann and Malacrino (2019)). Intuitively, unemployment risk associated with large earnings losses should rise 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 a 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. 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.

[16]We set τ equal to 2015 to capture the impact of the full development of the China shock. As seen in Figure A.5, $\Delta IP_{r\tau}$ increases sharply between 2000 and 2011 and only becomes relatively stable in the period 2011 to 2015. In Tables A.5 and A.6, in the Appendix, we run some robustness tests with other values for τ and results remain virtually the same. In Table A.6, we also vary the initial year of the shock, changing it to 1999 instead of 2000 and results remain robust.

measured in thousands of dollars per worker.

Figure 1 plots the distribution of ΔIP_r across the 509 Brazilian regions. As measured by ΔIP_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 1 that the largest import-penetration shocks occur in the most industrialized areas of the country: the South, the Southeast, 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.

Figure 1: Distribution of changes in Import Penetration (ΔIP_r)



Notes: The figure plots the distribution of variable ΔIP_r across Brazilian local labor markets. ΔIP_r measures changes in import penetration from 2000 to 2015, as defined by Equation 5. Values are measured in thousands of dollars per worker and plotted by quintiles.

3 Empirical Strategy

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

$$m[\Delta^n y^i_{r,t}] = \beta_1 \Delta IP_r + \beta_2 m[\Delta^1 y^i_{r,1999}] + W'_{r,2000}\delta + \alpha_a + \varepsilon_r, \tag{3}$$

where $m[\Delta^n y^i_{r,t}]$ defines moments from the distribution of income changes between t and $t+n$ of region r. Specifically, $m[\Delta^n y^i_{r,t}] \equiv m_{r,t}$ 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 t defines the initial period from which the distribution of income change is computed and n the difference between periods. In our baseline specification, we present results in which the final year (i.e., $t+n$) is set equal to 2015, and n is equal to 1, 3, and 5. The goal is to capture the impact of the full development of the China shock on the distribution of earnings risk. We set n equal to 1, 3, and 5 so our results are comparable to most of the earnings dynamics literature.

The term ΔIP_r defines the import penetration growth between the years 2000 and 2015, as described in Equation (2). In practice, following Autor et al. (2013), ΔIP_r is the change in Chinese import exposure per worker in a region, where imports are weighted according to the local labor markets' share in the national-industry employment. The variable $m[\Delta^1 y^i_{r,1999}]$ is the moment of the 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.[17]

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 than 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.[18]

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.[19] It is precisely this heterogeneity

[17] In Table A.7, in the Appendix, we also include $m[\Delta^5 y^i_{1995}]$, controlling for a longer-period pre-trend and finding virtually the same results. Results are also robust to excluding this term.

[18] Note that by including the share of employment in the agriculture, extractive, and manufacturing sectors, we are implicitly controlling for the nontradable sector. Hence, we are not subject to the incomplete shares problem described in Borusyak et al. (2022).

[19] As explained in Costa et al. (2016), this strategy is feasible because the distribution of Brazil–China

that allows the cross-sectional variation in trade exposure necessary for the identification.

Additionally, in our preferred specification, we include fixed effects α_a for the five main geographic areas in Brazil as defined by the Brazilian Institute of Geography and Statistics (IBGE): North, Northeast, Central-West, South, and Southeast. Each of these areas includes neighbor states that share similarities in terms of economic, social, and geographic characteristics. As observed in Figure A.1, the largest import penetration shocks are concentrated in the South and the Southeast 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.[20] 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 (3) 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. 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 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 subsectors), changes in internal patterns of consumption due to rising income, and inequality reduction or variations in world prices or quantities.

To deal with these potential confounders, we construct an instrument for ΔIP_r. To address the possibility of the existence of Brazil-specific sectorial trends, we follow the standard

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%).

[20] An alternative would be the inclusion of state fixed effects, as the preferred specification of Costa et al. (2016). The rationale for this is the existence of policies (for example, minimum wage and other labor market interventions) that may vary at the state level. However, note that, differently from Costa et al. (2016), who study the impact of trade shocks on wage and employment growth, we study the effects on the volatility. Thus, as explained in Section 2.1, we first compute residuals of a regression of log earnings on year and age dummies, and then, take the first difference between these residuals for each individual. These year dummies already clean region shocks common across workers, such as, for example, the effects of state or local-level policies on mean wage growth. Furthermore, our measure of volatility also controls for the effects of tenure or experience, for adjustments in labor market composition, and for time-invariant factors at the individual level that could affect the mean wage growth in the microregion. Therefore, the additional inclusion of state fixed effects in our regression would then, absorb part of the effects of import penetration on labor market *volatility*. But this is, precisely, part of the effect that we would like to capture. Indeed, in Tables A.8 and A.9 in the Appendix, we show a version of our main results with state fixed effects instead. Results follow a very similar pattern, but, in some, cases, are a little smaller in magnitude. Thus, since our measure of volatility is already cleaned from all the mean effects of state-level policies, we prefer to report our baseline results with the geographical areas fixed effects instead.

approach of the "China shock" literature (e.g., Autor et al. 2013, Krishna and Senses 2014 and many others) and use information on growth in trade between China and countries other than Brazil. In particular, we follow Costa et al. (2016), who use an approach that also deals with the possibility of correlated world-level shocks by using auxiliary regressions to 'clean out' changes in prices and quantities at the global level. Then, we construct an instrument for ΔIP_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 $\Delta\tilde{X}_{ij} = \tilde{X}_{ij,2015} - \tilde{X}_{ij,2000}$:

$$\frac{\Delta\tilde{X}_{ij}}{\tilde{X}_{ij,2000}} = \gamma_j + \delta_{Chinaj} + \mu_{ij} \tag{4}$$

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 γ_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 δ_{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 $\Delta\hat{I}_j = V_{CjB,2000}\hat{\delta}_{Chinaj}$. The instrumental variable is then constructed as follows:

$$iv\Delta IP_r = \sum_j \frac{L_{rj,2000}}{L_{Bj,2000}} \frac{\Delta\hat{I}_j}{L_{r,2000}} \tag{5}$$

By running the auxiliary regressions indicated in (4), 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. As explained by Costa et al. (2016), if Chinese trade with the rest of the world (excluding Brazil) had evolved in the same way as that of the (weighted) average country in each sector, $\Delta\hat{I}_j$ would be equal to zero for all sectors j. This is not what happens. $\Delta\hat{I}_j$ varies substantially across sectors, confirming that the trade of China with the rest of the world evolved in a different pattern than global trends over the same period. Intuitively, the "China fixed effect" for each sector j isolates the distinctive pattern of the China rise, which, as explained in Subsection 2.3 and in Autor et al. (2016), derives from Chinese sector-specific comparative advantages and internal factors. It is precisely the existence of this differential pattern that allows the estimation of δ_{Chinaj} and enables the identification strategy.

The key assumptions for the identification of a causal effect in our empirical strategy are the relevance condition and the exclusion restriction. We report the F-statistic of the first stage for every regression and the values are well beyond the recommended levels. For instance, the F-statistics reported in Table 4 are around 300 for all dispersion outcomes, confirming that we have a strong instrument. For the exclusion restriction to hold, we need the instrument to affect labor market volatility only through its effect on import penetration, conditional on controls. The substantial heterogeneity in the distribution of earnings growth in the year 2000 across regions (shown in Subsection 2.2) raises the concern about whether there are unobservable factors that affect both the exposure of a local labor market to the China shock and our measure of income risk. Although it is not possible to directly test the exclusion restriction, Appendix Figures A.3 and A.4 show that our import penetration instrument is not correlated with different moments of the distribution of one- and five-year earnings changes a decade prior to the China shock.[21] This provides evidence that the China shock is a valid instrument in our setting.

4 Empirical Results

Variance and dispersion. Table 3 presents results of Equation (3) 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 ΔIP_r increases the variance of one, three, and five-year income growth by 0.034, 0.063, and 0.082 respectively. In column (2), we add all sets of controls, as specified in the previous section. The estimated results decrease to 0.006, 0.023, and 0.032, respectively, revealing the importance of adding the covariates.

In columns (3) to (6), we present results from the instrumental-variable framework described in Section 3. Column (3) displays the estimated coefficients without covariates and the 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. 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 0.042, 0.03, and 0.012.

Then, column (5) includes the control for the baseline value of the variance of one-year

[21] The exceptions are the C.S. Kurtosis in Figure A.3 and the fraction of extreme positives in Figure A.4.

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

	OLS		IV			
	(1)	(2)	(3)	(4)	(5)	(6)
			$V[\Delta^5 y^i_{r,2010}]$			
ΔIP_r	0.082***	0.032***	0.081***	0.042***	0.040***	0.041***
	(0.011)	(0.007)	(0.010)	(0.008)	(0.007)	(0.006)
			$V[\Delta^3 y^i_{r,2012}]$			
ΔIP_r	0.063***	0.023***	0.062***	0.030***	0.028***	0.031***
	(0.011)	(0.007)	(0.010)	(0.007)	(0.006)	(0.006)
			$V[\Delta^1 y^i_{r,2014}]$			
ΔIP_r	0.034***	0.006	0.032***	0.012***	0.011**	0.013**
	(0.008)	(0.006)	(0.008)	(0.005)	(0.005)	(0.006)
Region Controls in 2000		Yes		Yes	Yes	Yes
$V[\Delta^1 y^i_{r,1999}]$		Yes			Yes	Yes
Geographic Area FE		Yes				Yes
Observations	509	509	509	509	509	509
1st Stage F-Stat			402.29	408.95	412.95	339.37

Notes: This table estimates the impact of import penetration ΔIP_r on the variance of five ($V[\Delta^5 y^i_{r,2010}]$), three ($V[\Delta^3 y^i_{r,2012}]$) and one-year ($V[\Delta^1 y^i_{r,2014}]$) income growth. Income growth is calculated so that 2015 is the final year. Region Controls in 2000 include: workers employed in the formal sector, the share of workers with high school and less than 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 $V[\Delta^1 y^i_{r,1999}]$ 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.

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 shows that the OLS estimation is slightly downward biased. Under our preferred specification (column 6), an increase in \$1000 per worker in ΔIP_r increases the variance of five, three, and one-year income growth by 0.041, 0.031, and 0.013. These figures represent an increase of around 6.8%, 6.1%, and 4.0% if compared to the national values in the baseline year. Importantly, in all the specifications of Table 2, the effects of ΔIP_r on $V[\Delta^5 y^i_{r,2010}]$ are larger than the effects on $V[\Delta^3 y^i_{r,2012}]$ and $V[\Delta^1 y^i_{r,2014}]$. As discussed in Appendix C and in Section 6, 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 remainder of the paper, we show only the results for the most robust specification (column 6).

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

	Variance	P9010	P9050	P5010
	$m[\Delta^5 y^i_{r,2010}]$			
ΔIP_r	0.041***	0.077***	0.006	0.071***
	(0.006)	(0.015)	(0.013)	(0.014)
	$m[\Delta^3 y^i_{r,2012}]$			
ΔIP_r	0.031***	0.059***	0.002	0.055***
	(0.006)	(0.020)	(0.013)	(0.017)
	$m[\Delta^1 y^i_{r,2014}]$			
ΔIP_r	0.013**	0.039*	0.003	0.033**
	(0.006)	(0.023)	(0.009)	(0.015)
Observations	509	509	509	509
1st Stage F-Stat	339.37	331.58	324.62	343.34

Notes: Using the IV framework, this table estimates the impact of import penetration ΔIP_r on the dispersion of five ($\Delta^5 y^i_{r,2010}$), three ($\Delta^3 y^i_{r,2012}$) and one-year ($\Delta^1 y^i_{r,2014}$) income growth. Income growth is calculated so that 2015 is the final year ($n+t$). All columns include region controls in 2000, a control for the baseline value of the one-year income growth of the respective moment ($m[\Delta^1 y^i_{r,1999}]$), and dummies for the five Brazilian macro-regions (specification of column (6) of Table 3). 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 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 ΔIP_r increases the difference between the 90^{th} and the 10^{th} percentile of $\Delta^5 y^i_{r,2010}$, $\Delta^3 y^i_{r,2012}$ and $\Delta^1 y^i_{r,2014}$ by 7.7, 5.9, and 3.9 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 ΔIP_r increased by 3.85 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.[22] The results from Table 4 display a clear message: the impact of ΔIP_r on dispersion is largely concentrated in the lower tail. Roughly, the effect on the $P5010$ accounts for 92% (0.071/0.077), 93% (0.055/0.059) and 85% (0.033/0.039) of the total effect of ΔIP_r on the P9010 of $\Delta^5 y^i_{r,2010}$, $\Delta^3 y^i_{r,2012}$ and $\Delta^1 y^i_{r,2014}$ respectively.

From the workers' perspective, the lower tail of the earnings growth distribution represents negative earnings changes, as the median of the distribution is close to zero. Hence, an increase in the lower tail without a substantial increase in the upper tail means that there is a higher risk of large earnings declines without an increase in the opportunities for large gains. For instance, an increase of 7.1 percentage points in the P5010 indicates that workers at the 10th percentile of the earnings growth distribution, who already face considerable negative earnings changes, now experience even larger differences in their earnings growth (i.e., 7.1 percentage points) relative to workers at the median of the distribution.

Asymmetry and Tails. Although the dispersion is a good starting point to understand how trade affects 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 log changes of 0.5 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. Recall that we can express the Kelley skewness as the share of the $P9010$ accounted by the $P9050$: $\mathcal{S}_K/2 + 0.5 = (P90 - P50)/(P90 - P10)$, implying that an increase of \$1000 per worker in ΔIP_r increases $(P90 - P50)/(P90 - P10)$ by $\beta/2$. Consequently, the coefficients from Table 5 indicate that a \$1000 increase in ΔIP_r reduces the fraction of the $P9010$ accounted by the $P9050$ in 2.4, 2.2 and 1.7 percentage points for $\Delta^5 y^i_{r,2010}$, $\Delta^3 y^i_{r,2012}$ and $\Delta^1 y^i_{r,2014}$ 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

[22] Note that the control $m[\Delta^1 y^i_{r,1999}]$ is set to be equal to $P9050[\Delta^1 y^i_{r,1999}]$ in the regression for the P9050 and $P5010[\Delta^1 y^i_{r,1999}]$ 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 5: Effect of Trade Shock on Asymmetry and Tails of Income Growth

	Kelley Skewness	$P(\Delta^n y_t^i > 0.5)$	$P(\Delta^n y_t^i < -0.5)$	C.S. Kurtosis
	$m[\Delta^5 y_{r,2010}^i]$			
ΔIP_r	-0.048**	0.001	0.011**	0.038
	(0.019)	(0.003)	(0.005)	(0.149)
	$m[\Delta^3 y_{r,2012}^i]$			
ΔIP_r	-0.044**	0.000	0.008**	-0.048
	(0.019)	(0.003)	(0.004)	(0.179)
	$m[\Delta^1 y_{r,2014}^i]$			
ΔIP_r	-0.034**	0.000	0.005*	-0.102
	(0.016)	(0.002)	(0.003)	(0.423)
Observations	509	508	508	509
1st Stage F-Stat	340.51	336.35	336.82	332.66

Notes: Using the IV framework, this table estimates the impact of import penetration ΔIP_r on the asymmetry and tails of the income growth distribution. C.S. kurtosis refers to Crow-Siddiqui kurtosis. Income growth is calculated so that 2015 is the final year $(n + t)$. All columns include region controls in 2000, a control for the baseline value of the one-year income growth of the respective moment ($m[\Delta^1 y_{r,1999}^i]$), and dummies for the five Brazilian macro-regions (specification of column (6) of Table 3). 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.

around 47.6% ($\mathcal{S}_K = -4.8$ and $P9050/P9010 = 47.6\%$). These results suggest that the distribution of income growth becomes more negatively skewed.

Table 5 also shows that an $1000 rise in ΔIP_r increases the share of individuals suffering negative income log changes lower than -0.5 by 1.1, 0.8 and 0.5 percentage points for $\Delta^5 y_{r,2010}^i$, $\Delta^3 y_{r,2012}^i$ and $\Delta^1 y_{r,2014}^i$ respectively. On the other hand, an increase in import penetration does not increase the share of individuals receiving positive income log changes larger than 0.5. Finally, we found no results of ΔIP_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. This is not inconsistent with the positive effects found in the share of large negative 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 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 A.10 shows that a \$1000 per worker increase in import penetration yields a decrease in the growth rate of income of 7.6 percentage points between 2000 and 2015 (column 1) and 3.9 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 not statistically significant). 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.[23]

5 Sources of Dispersion and Tails of Labor Income Growth

In the previous section, we established that trade shocks change the distribution of income growth, in particular at the lower tail of the distribution. What could explain the increase in the size of negative labor income shocks? The trade literature emphasizes that following a trade shock, there is a substantial reallocation of factors within and across industries and regions, particularly in and out of tradable sectors. This reallocation is often associated with unemployment shocks with large income losses for workers. In this section, we explore this argument further. For the sake of simplicity, the tables in this section contain results for the distribution of five-year changes.

Job, Industry and Region Switching. Recent literature has shown that the distribution of income growth of job switchers is more dispersed than the one of non-switchers (Halvorsen et al., 2023; Guvenen et al., 2021). This is particularly important in our context as the trade

[23] The fact that both papers find a negative impact of trade 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 the wages of formal and informal workers. Although they control for composition, their effects on wages might still suffer from selection issues. Our results, instead, are clean from 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 the wages of employed individuals highly attached to the formal labor market, 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 on wages are closer to their results for manufacturing workers only.

Table 6: Effect of Trade Shock on the Fraction of Switchers

	Fraction Job Switchers	*Fraction Ind. Switchers*	*Fraction Region Switchers*
ΔIP_r	0.015	0.031***	0.010
	(0.011)	(0.010)	(0.018)
Observations	509	509	509
1st Stage F-Stat	332.52	345.23	337.85

Notes: Using the IV framework, this table estimates the impact of import penetration ΔIP_r on the fraction of job, industry and region switchers between 2010 and 2015. All columns include region controls in 2000, a control for the baseline value of the one-year income growth of the respective moment ($m[\Delta^1 y^i_{r,1999}]$), and dummies for the five Brazilian macro-regions (specification of column (6) of Table 3). 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.

literature emphasizes the role of labor reallocation across employers and industries after a trade shock. To understand if reallocation explains the changes observed in the distribution of income growth in our setting, we first study whether the trade shock increases the fraction of job, industry, and region switchers. Then, we analyze the impact of import penetration on the distribution of income growth of switchers and stayers separately.[24]

Table 6 shows that an increase of \$1000 in ΔIP_r increases the fraction of industry switchers by 3.1 percentage points. A simple back-of-the-envelope calculation suggests that if the P9010 of switchers and non-switchers remained constant on their respective baseline values in 1995-2000, the increase in 3.1 p.p in the fraction of industry switchers would have an impact of $0.031 \times (2.53 - 1.06) = 0.045$ on the overall P9010, a little more than half of the coefficient reported in Table 4. The impact of import penetration on the fraction of job and region switchers is, on the other hand, quantitatively smaller and not statistically significant.

Table 7 shows that the import penetration shock increases the dispersion of income growth for individuals who switch jobs and industries compared to those who remain in their initial positions. Notably, this effect is more pronounced in the lower end of the earnings growth distribution (P5010), indicating that switching jobs and industries is associated with negative earnings shocks. This finding aligns with the notion of costly factor reallocation following a

[24] A job (industry, region) switcher is defined as an individual employed in a different firm (industry, region) in time t and in $t+n$. Recall that each individual is assigned a unique employer, industry, and region per year. In case the individual had multiple employment spells, the industry, employer, and region with the largest spell is assigned. In the case of ties, the largest total labor income is used as a tie-breaker. Between 1995-2000, the fraction of job, industry, and region switchers was 47.9%, 30.3%, and 11.9% respectively. As in the literature, the distribution of income growth of switchers is more dispersed than the distribution of non-switchers in Brazil. For example, the P9010 of the income growth distribution between 1995-2000 of industry switchers is 2.53, while for the non-switchers it is 1.06.

Table 7: Effect of Trade Shock on the Dispersion of the Distribution of Income Growth: Job and Industry Switchers and Stayers

	P9050	P5010	P9050	P5010	P9050	P5010
	Job Switchers		*Industry Switchers*		*Region Switchers*	
ΔIP_r	0.013	0.070***	0.009	0.062***	-0.023	0.027*
	(0.011)	(0.021)	(0.015)	(0.019)	(0.020)	(0.015)
Observations	509	509	508	508	509	509
1st Stage F-Stat	329.64	337.01	328.32	332.60	339.84	337.82
	Job Stayers		*Industry Stayers*		*Region Stayers*	
ΔIP_r	-0.018	0.024***	-0.016	0.007	0.013	0.066***
	(0.017)	(0.008)	(0.015)	(0.009)	(0.020)	(0.019)
Observations	509	509	509	509	509	509
1st Stage F-Stat	332.49	345.27	325.40	340.21	319.53	350.50

Notes: Using the IV framework, this table estimates the impact of import penetration ΔIP_r on the dispersion of five-year($\Delta^5 y^i_{r,2010}$) income growth of job, industry and region switchers, and job, industry and region stayers. Income growth is calculated between 2010 and 2015. All columns include region controls in 2000, a control for the baseline value of the one-year income growth of the respective moment ($m[\Delta^1 y^i_{r,1999}]$), and dummies for the five Brazilian macro-regions (specification of column (6) of Table 3). 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.

trade shock.[25] One particular exception is the region switchers. The impact of the import penetration shock on the P5010 of the distribution of region stayers is *larger* relative to the region switchers, suggesting that migration serves as an insurance mechanism against trade shocks.

Hours and Wages. Our analysis thus far has revealed that the increase in earnings risk is attributed to a rise in the dispersion and asymmetry of earnings growth among individuals who switch jobs and industries, as well as an increase in the likelihood of industry switching. Switchers often experience periods of unemployment between jobs, which introduces additional sources of earnings risk, particularly the prolonged unemployment duration. In general, labor income can be decomposed into the sum of hourly wages (w^i_t) and annual hours worked (h^i_t): $y^i_t = w^i_t + h^i_t$. Annual hours, in turn, can be further decomposed into

[25] Appendix Table A.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.

weeks worked (extensive margin) and weekly hours (intensive margin). Unfortunately, as explained in Section 2, our data only covers contractual hours and not actual hours worked, limiting our ability to analyze the intensive margin of annual hours. To test whether wages or annual hours are responsible for the increase in dispersion of annual income growth, we estimate our baseline specification with the variance of wages and hours as the dependent variable for job, industry, and region switchers, as well as stayers.[26]

Table 8: Effect of Trade Shock on Variance of Wages and Hours for Five-year Growth Distributions

	$V[\Delta^5 w^i_{r,2010}]$	$V[\Delta^5 h^i_{r,2010}]$	$V[\Delta^5 w^i_{r,2010}]$	$V[\Delta^5 h^i_{r,2010}]$	$V[\Delta^5 w^i_{r,2010}]$	$V[\Delta^5 h^i_{r,2010}]$
	Job Switchers		*Ind. Switchers*		*Region Switchers*	
ΔIP_r	0.009	0.024***	0.004	0.020**	-0.007	-0.001
	(0.007)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)
Observations	508	508	505	505	508	508
1st Stage F-Stat	328.00	324.73	325.46	325.68	340.39	315.07
	Job Stayers		*Ind. Stayers*		*Region Stayers*	
ΔIP_r	-0.006	-0.000	-0.006	-0.004	0.006	0.016
	(0.008)	(0.010)	(0.007)	(0.010)	(0.008)	(0.017)
Observations	509	509	509	509	509	509
1st Stage F-Stat	336.63	337.02	336.38	336.76	341.23	336.36

Notes: Using the IV framework, this table estimates the impact of import penetration ΔIP_r on the variance of five-year wages and hours growth. The growth rate is calculated between 2010 and 2015. All columns include region controls in 2000, a control for the baseline value of the one-year income growth of the respective moment ($m[\Delta^1 y^i_{r,1999}]$), and dummies for the five Brazilian macro-regions (specification of column (6) of Table 3). 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 8. In all cases, the coefficients for the stayers are small and not statistically significant. For the switchers, particularly job and industry switchers, the increase in the variance of the distribution of five-year changes in annual hours is between three to five times larger than the associated coefficients of the variance of changes in hourly wages. This shows that the impact of import penetration on the variance of idiosyncratic earnings growth can be largely explained by the increase in the volatility in hours worked annually.

Job Separation. The previous findings indicate that the increase in earnings risk resulting from the China shock can be attributed to an increase in the variance of hours among

[26]Note that we can decompose the variance of income changes in three terms: $V(\Delta^n y^i_t) = V(\Delta^n w^i_t + \Delta^n h^i_t) = V(\Delta^n w^i_t) + V(\Delta^n h^i_t) + 2 \times COV(\Delta^n w^i_t, \Delta^n h^i_t)$. Results using the covariance as the dependent variable are available under request.

individuals who switch jobs and industries. This is likely a consequence of the involuntary labor reallocation that follows such shocks, as workers often experience longer periods of unemployment after involuntary separations. To directly test this hypothesis, we use the information available in RAIS regarding the type of job separation (layoffs or quits).[27]

Table 9: Effect of Trade Shock on Dispersion by Type of Separation

	Layoffs		Quits		No Separations	
	P9050	P5010	P9050	P5010	P9050	P5010
ΔIP_r	0.008	0.067***	0.024*	0.005	-0.015	0.010
	(0.018)	(0.024)	(0.013)	(0.014)	(0.015)	(0.007)
Observations	509	509	509	509	509	509
1st Stage F-Stat	338.34	333.84	345.84	331.78	329.10	330.43

Notes: Using the IV framework, this table estimates the impact of import penetration ΔIP_r on the dispersion of five-year($\Delta^5 y^i_{r,2010}$) income growth by type of job separation. Income growth is calculated between 2010 and 2015. All columns include region controls in 2000, a control for the baseline value of the one-year income growth of the respective moment ($m[\Delta^1 y^i_{r,1999}]$), and dummies for the five Brazilian macro-regions (specification of column (6) of Table 3). 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 workers who experienced involuntary separations in regions exposed to the import penetration shock faced an increase in earnings risk. The earnings growth distribution for this group becomes more dispersed, particularly at the lower end, indicating larger negative idiosyncratic income shocks. Note that nonemployment spells with negative persistent effects usually generate left-skewness. Otherwise, a negative shock followed by a positive one of similar size leaves the symmetry of the distribution unaffected. The distribution of earnings growth for workers who had voluntary separations or no separations between 2010 and 2015, in contrast, does not exhibit any notable effects on the lower tail of the distribution. This finding, in conjunction with previous results, emphasizes the significance of the increase in unemployment spells, particularly for individuals switching industries, in explaining the observed increase in negative earnings risk documented in Section 4.

Heterogeneity by Individual Characteristics. An interesting question is whether the rise in earnings risk was concentrated in some particular groups. In our case, one would ask if workers initially employed in tradable industries in exposed regions faced higher earnings

[27] Specifically, we compute the earnings growth distribution for three distinct groups of workers based on their job separation history: (i) the ones who recorded at least one layoff between t and $t+n$; (ii) the ones who recorded at least one quit between t and $t+n$ (and no layoffs); (iii) the ones who recorded no separations.

risk after the China shock. Table 10 shows that workers in both tradable and non-tradable sectors experience an increase in the negative idiosyncratic income shocks after a trade shock (a rise in the P5010). In the case of the tradable industries, however, we observe a decline in the right tail (the P9050). Since the change in both the positive and negative tails are similar in magnitude, the total increase in the P9010 for the tradable sector is zero. It is evident, however, that this average zero effect on total dispersion masks that the distribution of earnings growth is changing with a large increase in negative income shocks. The fact that the skewness becomes more negative, even though the dispersion remains constant, points to the importance of looking at higher moments when evaluating earnings risk.

The decline observed in the right tail of earnings growth distribution in tradable industries following the China shock indicates a reduction in positive earnings shocks for workers initially employed in these industries in exposed regions. This implies that these workers are unable to experience earnings gains, either due to their inability to transition out of tradable industries with higher earnings or their limited upward mobility within the same industries. This decrease in the dispersion of positive shocks, combined with the simultaneous increase in the dispersion of negative shocks, characterizes a third-moment shock in the earnings risk distribution.

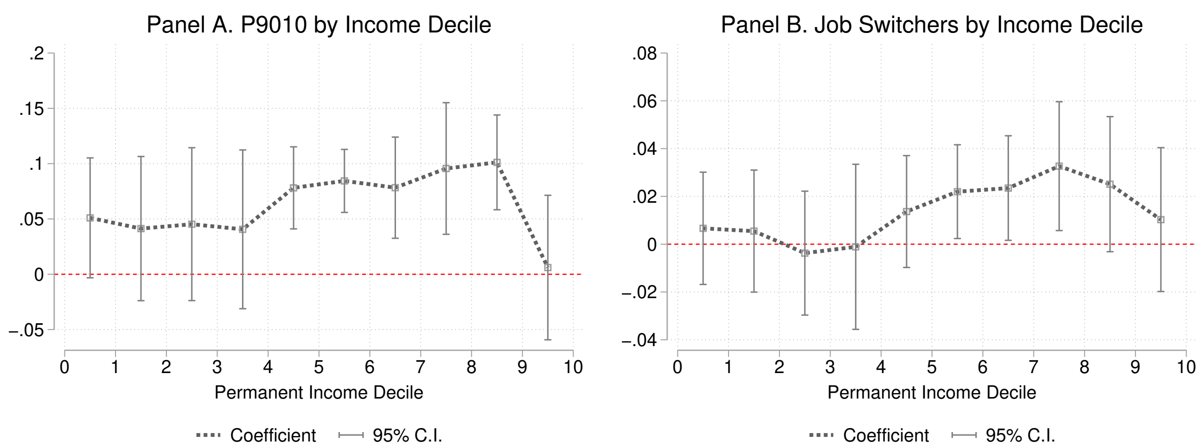
Table 10: Effect of Trade Shock on Dispersion of Income Growth by Tradable and Non-tradable Industries

	Variance	P9010	P9050	P5010
	Tradable			
ΔIP_r	-0.015	0.006	-0.063***	0.058*
	(0.014)	(0.039)	(0.018)	(0.031)
Observations	509	509	509	509
1st Stage F-Stat	327.16	336.62	336.98	336.84
	Non-Tradable			
ΔIP_r	0.039***	0.071***	0.023*	0.050***
	(0.009)	(0.018)	(0.013)	(0.018)
Observations	504	506	506	506
1st Stage F-Stat	325.77	298.74	312.97	316.39

Notes: Using the IV framework, this table estimates the impact of import penetration ΔIP_r on the dispersion of five-year income growth. Income growth is calculated so that 2015 is the final year ($n + t$). All columns include region controls in 2000, a control for the baseline value of the one-year income growth of the respective moment ($m[\Delta^1 y^i_{r,1999}]$), and dummies for the five Brazilian macro-regions (specification of column (6) of Table 3). 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 addition, the income dynamics literature highlights that earnings risk is heterogeneous and non-monotonic across the earnings distribution and age groups (Guvenen et al., 2021; Arellano et al., 2017; Karahan and Ozkan, 2013). To test whether the trade shock had heterogeneous effects across the earnings distribution, we run our baseline specification for each decile of the permanent income distribution (i.e., the average income between $t-1$ and $t-4$ net of age, year, and region dummies). Panel A of Figure 2 displays a non-monotonic effect. The impact is positive and gradually increases around the fourth decile, reaching its peak at the ninth decile, and subsequently dropping to zero for workers in the top decile. In our sample, similar to the literature, earnings volatility is higher for low-income workers. Then, why are upper-middle-class workers the ones most affected by the trade shock? Panel B of Figure 2 offers a possible explanation. After applying our baseline specification to the fraction of job switchers for each decile, we observe that the trade shock increases the likelihood of triggering a job switch for upper-middle-class workers, with minimal effects for low-income and top-decile workers. As discussed in the previous sections, the increase in the probability of switching jobs and industries constitutes one of the contributing factors to the increased earnings risk following the China shock.

Figure 2: Estimated Coefficient for the P9010 and the Job Switchers by Deciles of Permanent Income



Notes: Panel A plots the impact of import penetration ΔIP_r on the P9010 of five-year income growth, $P9010[\Delta^5 y^i_{r,2010}]$, by deciles of the permanent income, while Panel B plots the impact of ΔIP_r on the fraction of job switchers from 2010 to 2015 by deciles of the permanent income. 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.

Finally, we also split our sample into two skill groups (high and low) and two age groups (old and young).[28] Again, the baseline earnings volatility is higher for low-skill, and young workers, but the effect of the China shock is slightly larger for the high-skill group. There is no substantial difference among young and old workers. Appendix Table A.12 shows the estimates of our baseline specification using the P9050 and P5010 of the five-year earnings change distribution. Similarly to the baseline results, in all groups, the increase in dispersion is accounted for by an increase in the left tail (P5010) of the distribution.

6 Transition Dynamics of Idiosyncratic Shocks

An important question for the trade literature is whether the increase in the labor market volatility following a trade shock is (i) a temporary consequence of the redistribution of factors across industries and regions or (ii) a permanent shift in the overall volatility of labor markets due to heightened exposure to international shocks. In our particular case, it is also important to distinguish if the increase in the labor market risk is due to persistent idiosyncratic shocks, which usually leave scarring effects with pervasive welfare consequences to workers, or transitory idiosyncratic shocks. To differentiate between a temporary *trade* shock and a transitory *idiosyncratic* shock, imagine the labor market in a region with high import penetration. A temporary trade shock increases the reallocation of jobs, the fraction of large earnings changes, and involuntary separations during a transition period. Afterward, the earnings change distribution of the region reverts to normal. However, some workers in that region, during the transition period, might have received *persistent* idiosyncratic shocks, impacting their earnings trajectory for a long time. In this section, we exploit the cumulative structure of the variance of income growth to shed light on these two issues.

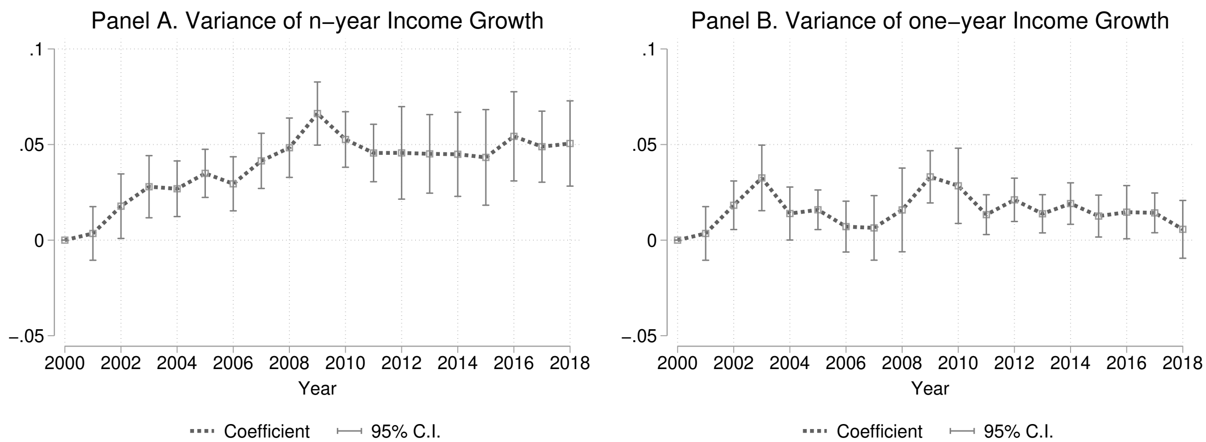
Through the lens of a permanent-transitory stochastic process, the income difference between t and $t+n$ is the sum of the history of persistent shocks between these periods and the two transitory shocks in time t and $t+n$ (see Equation (C.3) in the Appendix Section C). This implies that the variance of income growth has a cumulative structure: as n increases, the variance of $\Delta^n y_t$ grows larger, as long as the variances of transitory shocks are time-invariant. Intuitively, it also means that if import penetration has a stronger and persistent effect on the permanent idiosyncratic risk, the variance of $\Delta^n y_t$ will increase *faster* with n in regions highly affected by trade competition.[29]

[28] High-skill workers are the ones who completed high school or more and low-skill workers are the ones with less than high school. Young workers are the ones with 38 years old or less and old workers are the ones older than 38.

[29] One can see that by taking the difference of the variances between n and $n-1$ in a fully permanent-transitory stochastic process (i.e., Equation (C.3)): $V(\Delta^n y_t) - V(\Delta^{n-1} y_t) = \sigma^2_{\eta,t+n} + \sigma^2_{\varepsilon,t+n} - \sigma^2_{\varepsilon,t+n-1}$. Hence, the final argument lies in two assumptions. First, it requires that the persistent shock is fully permanent ($\rho = 1$). Second, it assumes that the effect on the transitory shock is constant across time.

To test this argument, we estimate the baseline model on the variance of n-year income growth starting in 2000, $V[\Delta^n y^i_{r,2000}]$, using $n = 1$ and progressively increasing until $n = 18$. Panel A in Figure 3 plots the coefficients for the estimated regressions. The coefficients become gradually more positive from 2003 to 2009 (the years in which our trade-exposure measure grew faster according to Figure A.5), peaking at 0.06 in 2009 and remaining relatively constant afterward.

Figure 3: Estimated Coefficient for the Variance of n-year and one-year Income Growth



Notes: Panel A plots the impact of import penetration ΔIP_r on the variance of n-year income growth, $V[\Delta^n y^i_{r,2000}]$ from $n = 1$ to $n = 18$, while Panel B plots the impact of ΔIP_r on the variance of one-year income growth, $V[\Delta^1 y^i_{r,t}]$ from $t = 2000$ to $t = 2017$. 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 relatively 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 $t + 1$ and the variances of the transitory shock at $t + 1$ and t. Thus, the relative stability of the coefficients in the period 2002-2018 provides convincing suggestive evidence that the

If $\sigma^2_{\varepsilon,t+n} = \sigma^2_{\varepsilon,t+n-1}$, the difference of the variances between n and $n - 1$ fully identifies the permanent component. Both assumptions are somewhat restrictive, so we take this result as merely illustrative. We pursue a fully transitory-persistent decomposition in Section 7.

transitory shock is time-invariant and that the increase in the idiosyncratic risk of affected local labor markets can be primarily attributed to the permanent risk.

Furthermore, the two panels offer insights into whether the volatility of the idiosyncratic shock in exposed labor markets increased permanently after the China shock or returned to pre-China shock levels. As previously explained, the fact that the variance of $n-$year income growth increases faster in highly-exposed regions between 2000 and 2010 provides evidence of higher variance in persistent idiosyncratic shocks during that period. Conversely, the flattening out of the coefficients after 2010 in Panel A of Figure 3 suggests that the difference between high and low-import penetration regions may have reverted to its pre-China shock level.

One possible caveat of our analysis is that we compute earnings growth for individuals over long periods, with the most extreme case involving periods 18 years apart. These individuals are likely to be highly attached to the labor market and less susceptible to large idiosyncratic shocks. As a robustness check, we conduct a similar analysis in Appendix Figure A.6 by using the year 2010 as the initial reference point. Once again, we observe that most of the increase in the coefficient occurred between 2010-2012 when the China shock was still in effect, while the growth of the coefficients for n-year variance levels off entirely between 2016 and 2018. Additionally, we run our baseline specification using as dependent variables the variance of earnings growth between 2013-2018 and 2015-2018, which represent the most recent years for calculating five and three-year earnings growth in our data. Although the coefficients remain positive and statistically significant, they are approximately 25% smaller compared to the coefficients presented in Table 4 (which uses as a dependent variable the variance of earnings growth between 2010-2015 and 2012-2015). Notably, the coefficient associated with earnings growth between 2017-2018 is not statistically significant.

Finally, although these findings could be taken as evidence that most of the increase in (persistent) idiosyncratic risk was temporary and primarily stemmed from the broad reallocation of labor following the trade shock, we acknowledge that our argument works under the assumption that the persistent component of the idiosyncratic shock is fully permanent (i.e., the AR(1) has a unit root). If idiosyncratic shocks are not sufficiently persistent, we cannot reject the possibility that there was a permanent shift in the stationary variance of the n-year income growth in regions exposed to the trade shock. A throughout investigation would need to estimate an income process with time and region-varying factors. We leave this avenue for future research.

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.

In the first step, we estimate a stochastic income process augmented to account for higher-order risk targeting moments from workers with high school or more (i.e., high skill) and less than high school (i.e., low skill). For each group of workers, we estimate the stochastic process twice. The first income process is estimated by targeting empirical moments (i.e., P9010, $P(\Delta^n y_t^i < -0.5)$, etc.) of the distribution of income changes using a national sample of workers from 1995 to 2000.[30] 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 the import penetration, ΔIP_r, from 2000 to 2015 times the estimated coefficients of the previous sections.[31]

Second, we input both the pre-China and the counterfactual income process in a standard partial equilibrium incomplete-markets model 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. We perform the analysis for both high and low-skill workers.

7.1 The Income Process

We perform a full permanent-transitory decomposition of the idiosyncratic risk by estimating a parsimonious version of the process established in Guvenen et al. (2021) 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:

[30] Alternatively, one could estimate targeting the moments of each local labor market separately. When targeting these moments, the results did not change substantially.

[31] In the counterfactual moments, we also include the average increase of the export penetration, ΔEP_r, computed in the Online Appendix B. For example, the $P9010[\Delta^5 y^i_{1995}]$ of high-skill workers is equal to 1.375. The post-China counterfactual P9010 is calculated as $P9010[\Delta^5 y^i_{CF}] = 1.375 + 0.467 \times 0.0853 + 0.562 \times 0.0011 = 1.415$, where 0.467 and 0.564 are the average increase of ΔIP_r and ΔEP_r. In practice, most of the coefficients of ΔEP_r are an order of magnitude smaller than the ones from ΔIP_r, and therefore are irrelevant for the estimation.

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

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

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

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

The econometric model includes a permanent component modeled as a unit root with iid innovations η_t^i and an iid transitory innovation ε_t^i, both drawn from a mixture of normal distributions.[32] 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 higher-order moments. We restrict the mean in levels of both the persistent and transitory innovations to unity: $\mathbb{E}[\exp\{\eta_t^i\}] = 1$ and $\mathbb{E}[\exp\{\varepsilon_t^i\}] = 1$. 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 $\mathbb{E}[\exp\{\eta_t^i\}] = 1$ and $\mathbb{E}[\exp\{\varepsilon_t^i\}] = 1$ respectively.

Finally, we estimate the parameters $\Theta \equiv (\mu_{\eta,1}, \sigma^2_{\eta,1}, \sigma^2_{\eta,2}, p_\eta, \mu_{\varepsilon,1}, \sigma^2_{\varepsilon,1}, \sigma^2_{\varepsilon,2}, p_\varepsilon)$ 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 log changes higher than 0.5, $P(\Delta^n y^i > 0.5)$, and lower than -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. We carry on the Simulated Method of Moments by giving equal weight to all the n-year differences. 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 D.

Table 11 presents the estimated parameters of the stochastic processes.[33] 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. Also, the implied moments of the mixtures are in line with the moments of the one and five-year distributions of earnings growth (see Appendix Table A.13). While the permanent component tends to be closer to normality

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

[33] See Appendix Table A.14 for the model fit to the targeted moments.

Table 11: Estimated Parameters

Scenario	p_η	$\mu_{\eta,1}$	$\mu_{\eta,2}$	$\sigma_{\eta,1}$	$\sigma_{\eta,2}$	p_ε	$\mu_{\varepsilon,1}$	$\mu_{\varepsilon,2}$	$\sigma_{\varepsilon,1}$	$\sigma_{\varepsilon,2}$
					High-skill workers					
pre-"China"	0.0470	0.1383	-0.0206	0.0004	0.1629	0.9048	0.0683	-1.2433	0.0264	0.4846
	(0.0074)	(0.0134)	.	(0.0079)	(0.0038)	(0.0010)	(0.0006)	.	(0.0118)	(0.0864)
Counterfactual	0.4355	0.0265	-0.0472	0.0711	0.2200	0.9295	0.0533	-1.5160	0.0815	0.3276
	(0.0081)	(0.0041)	.	(0.0077)	(0.0043)	(0.0006)	(0.0006)	.	(0.0023)	(0.0430)
					Low-skill workers					
pre-"China"	0.7356	0.0168	-0.0864	0.0047	0.2756	0.9012	0.0773	-1.517	0.0953	0.1401
	(0.0031)	0.0006	.	(0.0034)	(0.0030)	(0.0004)	(0.0003)	.	(0.0016)	(0.0238)
Counterfactual	0.6725	0.0229	-0.0825	0.0042	0.2596	0.9002	0.0798	-1.6412	0.1044	0.2109
	(0.009)	(0.0016)	.	(0.0068)	(0.0060)	(0.0006)	(0.0006)	.	(0.0028)	(0.0224)

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 ΔIS_r and ΔEP_r from 2000 to 2015. Bootstrap standard errors in parenthesis (300 replications).

with relatively low variance, the transitory component follows a more negatively skewed distribution.

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 economy is characterized by a continuum of agents indexed by i, who can be of high or low skill, $s \in \{h, l\}$. An individual is born and works until the age T_w, at which point they enter the retirement period. At age T, the individual dies with certainty. During the working period, workers earn gross labor income w_t^i, which is a function of a deterministic age-profile $\kappa_{s,t}$, and the stochastic term y_t^i, defined in Equation (6): $w_t^i = \exp\{\kappa_{s,t} + y_t^i\}$. The gross labor income is translated to net labor income, $\tilde{w}_t^i$, using a function designed to mimic the Brazilian tax system $\tilde{w}_t^i = G(w_t^i)$.[34] 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 return r, but are not allowed to borrow. They are born with no wealth. The individual problem is specified below:

[34]The function replicates the statutory bracket values of the income tax and social security contribution in Brazil in 2000 and includes an income floor calibrated to the unemployment insurance of a worker that earns the minimum wage in a full-time job. It is fully described in Online Appendix E.

$$\max_{\{c_t^i, a_{t+1}^i\}_{t=1}^T} \mathbb{E}_0 \sum_{t=1}^{T} \beta^{t-1} u(c_t^i),$$

$$\begin{aligned} \text{s.t.} \qquad & c_t^i + a_{t+1}^i = (1+r)a_t^i + \tilde{w}_t^i \qquad \text{if } t \leq T_w, \\ & c_t^i + a_{t+1}^i = (1+r)a_t^i + p^i \qquad \text{if } t > T_w, \\ & a_t \geq 0, \qquad \text{and} \qquad a_1 = 0. \end{aligned}$$

Calibration. The model period is one year. Individuals enter the labor market at age 27, retire at age 56 ($T_w = 29$) and die at age 75 ($T = 49$). 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 β to match a wealth-to-income ratio of 2.5. 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 deterministic age-earnings profile, $\kappa_{s,t}$, is estimated using a full set of dummies from a national sample from 1995-2000. Finally, we introduce initial heterogeneity in labor income $\sigma_{s,z0}$ and calibrate it to match the cross-sectional variance of gross labor income at age 27. The income process, the deterministic income profile, and the initial heterogeneity are skill-specific. All the other parameters are the same for both high and low-skill workers.

Welfare. We assess the welfare cost of the increase in risk by calculating the consumption equivalent variation (CEV) that makes an 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 such as volatility and asymmetry, abstracting from changes in wage levels and other channels.[35]

Table 12: Welfare Cost of Labor Earnings Risk

Counterfactual	High-skill Workers	Low-skill Workers
Steady state	-1.76%	-0.71%
Transition (newborns)	-1.22%	-0.59%
Transition (mid-careers)	-1.10%	-0.26%
Transition (old workers)	-0.52%	-0.07%

[35]We keep all other parameters constant, except the pension replacement rate which is recalibrated such that the average pension is the same across all the experiments.

We conduct four counterfactual experiments for each skill group and present their CEV in Table 12. In the first experiment, we assume that the change in earnings risk from China is permanent and we perform the comparison across two steady states. In this scenario, a newborn high-skill agent is willing to give 1.76% of her consumption instead of living her entire life in the riskier, post-China labor market. The welfare cost for a newborn low-skill worker is lower, amounting to 0.71% of consumption. This is due to the fact that the causal effect of the China shock is lower in magnitude for this group (see Appendix Table A.12).

In Section 6, we find evidence that the increase in earnings risk triggered by the China shock might be temporary. If that is the case, assuming a permanent change overstates the welfare losses of the increase in earnings risk. To account for that possibility, we compute the CEV of an unexpected and transitory change in the income process. Specifically, we assume that the economy is in the pre-China steady state and receives an unexpected shock that changes the income process of workers to the "counterfactual" scenario. This shock lasts a decade when the economy fully reverts to the pre-China level.[36] We compute the CEV for three types of workers: (i) newborns, who experience the China shock in their first ten years in the labor market; (ii) mid-careers, who are hit when they are age 38; (iii) and old workers, who experience the shock in their last ten years in the labor market. Even though the increase in risk is assumed to be the same for all workers, welfare losses are larger for younger workers, underscoring the importance of self-insurance as a mechanism to buffer the increase in risk stemming from a trade shock.

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.

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. In the case of asymmetry, higher exposure to the trade shock leads to a disproportionate increase in the fraction of workers receiving

[36] Once the economy is hit by the shock, workers fully forecast the dynamics of the shock. We abstract from equilibrium effects and leave prices as constants.

large negative shocks, and to a more negatively skewed distribution. We show, then, that the increase in the dispersion of earnings risk can be attributed to a rise in the fraction of industry switchers, and to an increase in the variance of hours worked among individuals who switch jobs and industries. This is a consequence of the involuntary labor reallocation that follows trade shocks, as workers often experience longer periods of unemployment after layoffs.

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 1.75% of consumption to avoid the riskier labor market depending on her characteristics. Under the assumption that the trade shock is temporary, the welfare costs are concentrated on young workers.

This paper is the first to exploit the regional distribution of a 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 income dynamics literature. 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 there are spillover effects on risk-sharing across regions is a question that remains unanswered and is an avenue for future research.

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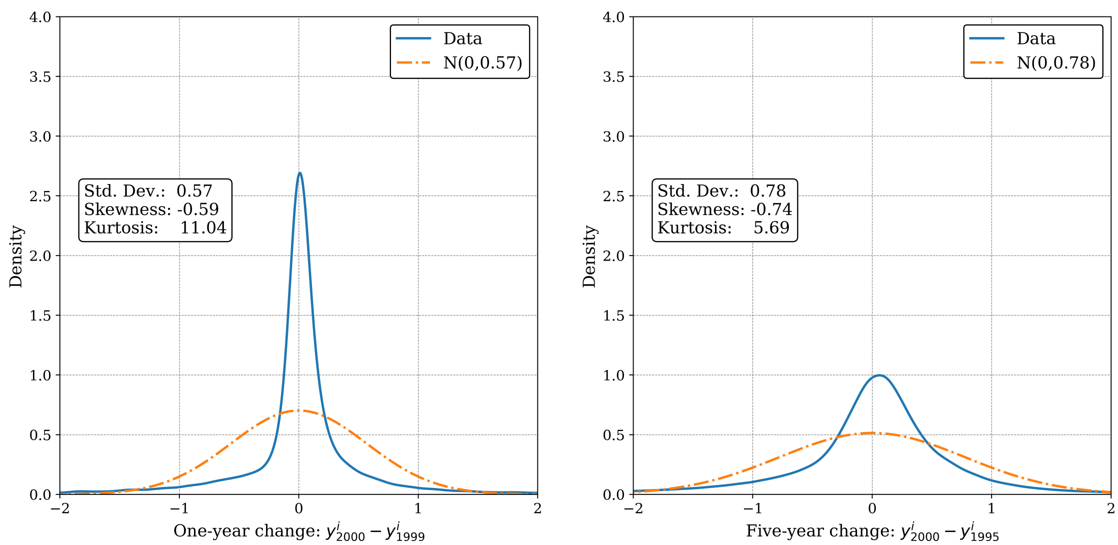
Online Appendix

Trade Shocks and Higher-Order Earnings Risk in Local Labor Markets

Tomás R. Martinez, Ursula Mello

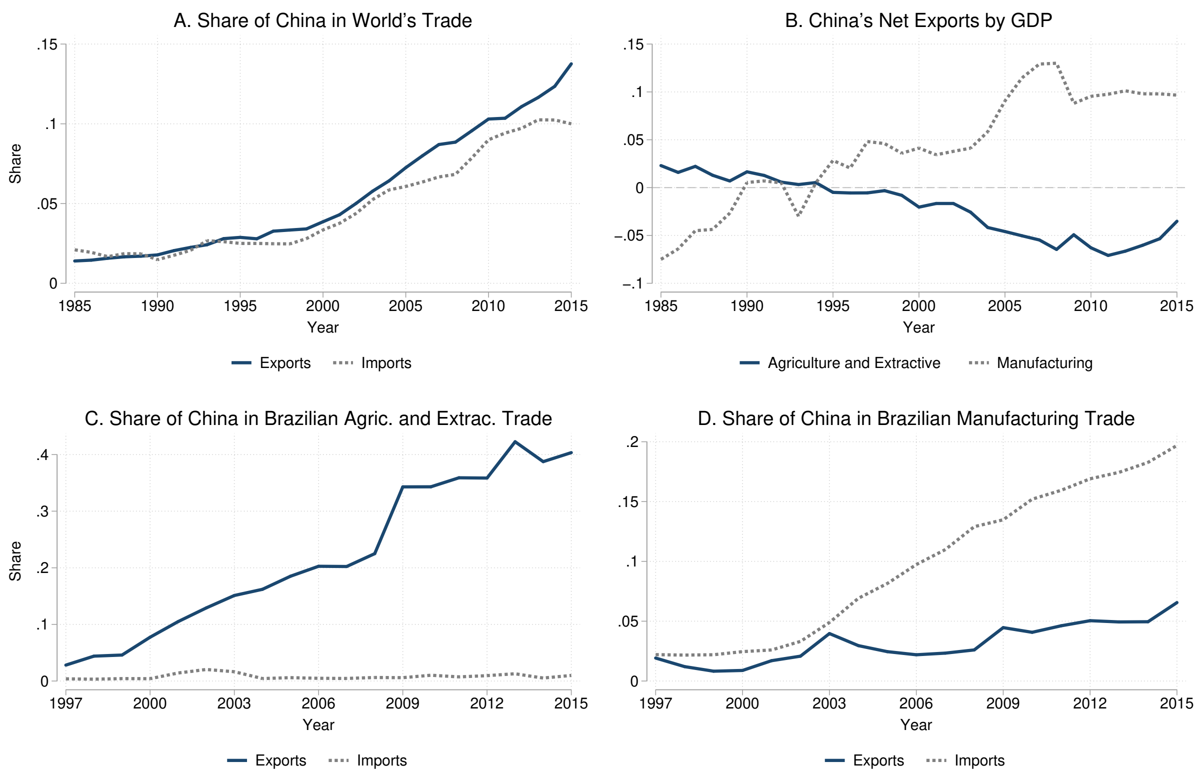
A Additional Figures and Tables

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



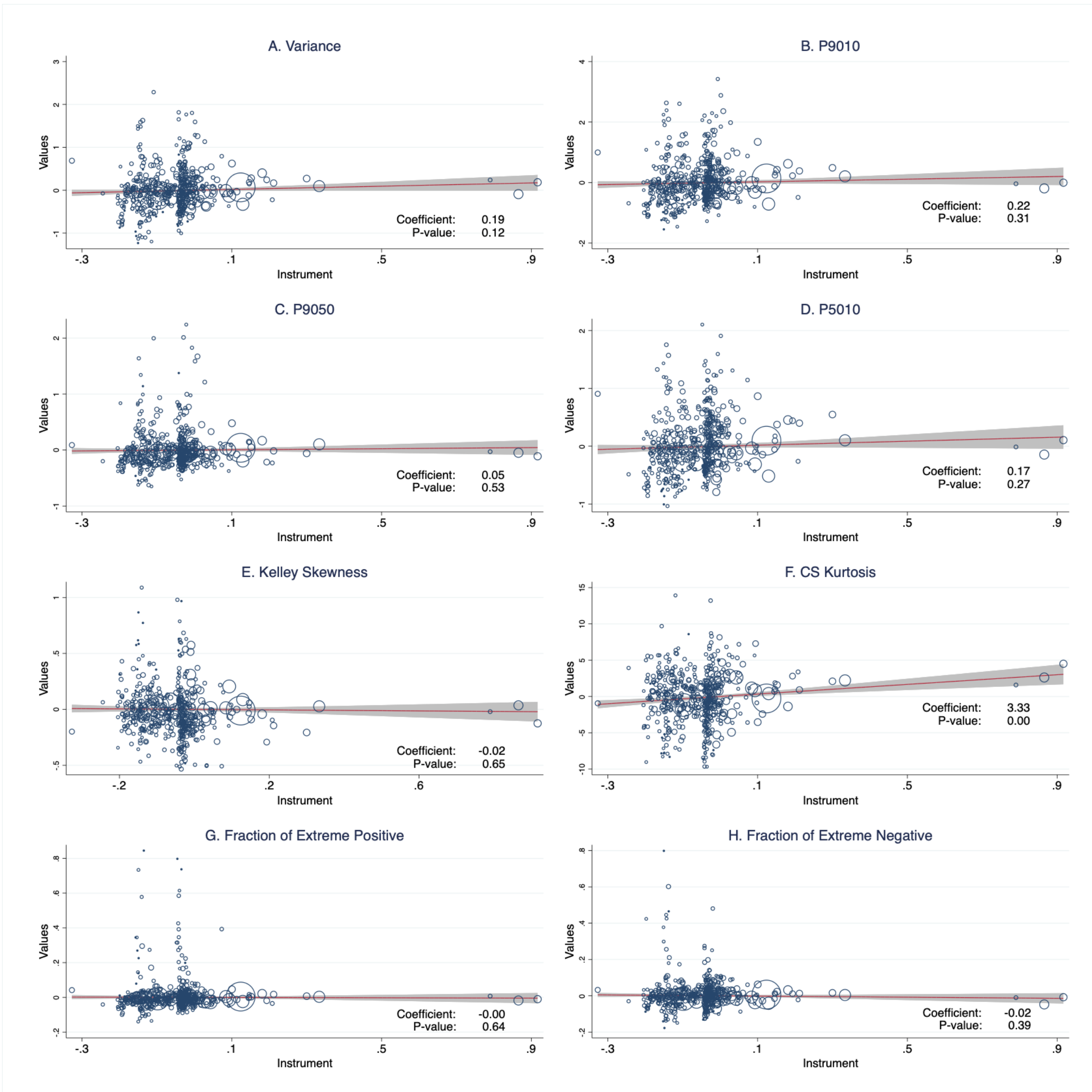
Notes: The distribution is computed using 1,000,000 individuals from a national sample. The growth rate is taken between the years of 2000-1999 and 2000-1995. The density is computed using a Gaussian Kernel with bandwidth equal to 0.05.

Figure A.2: The rise of China in International Trade



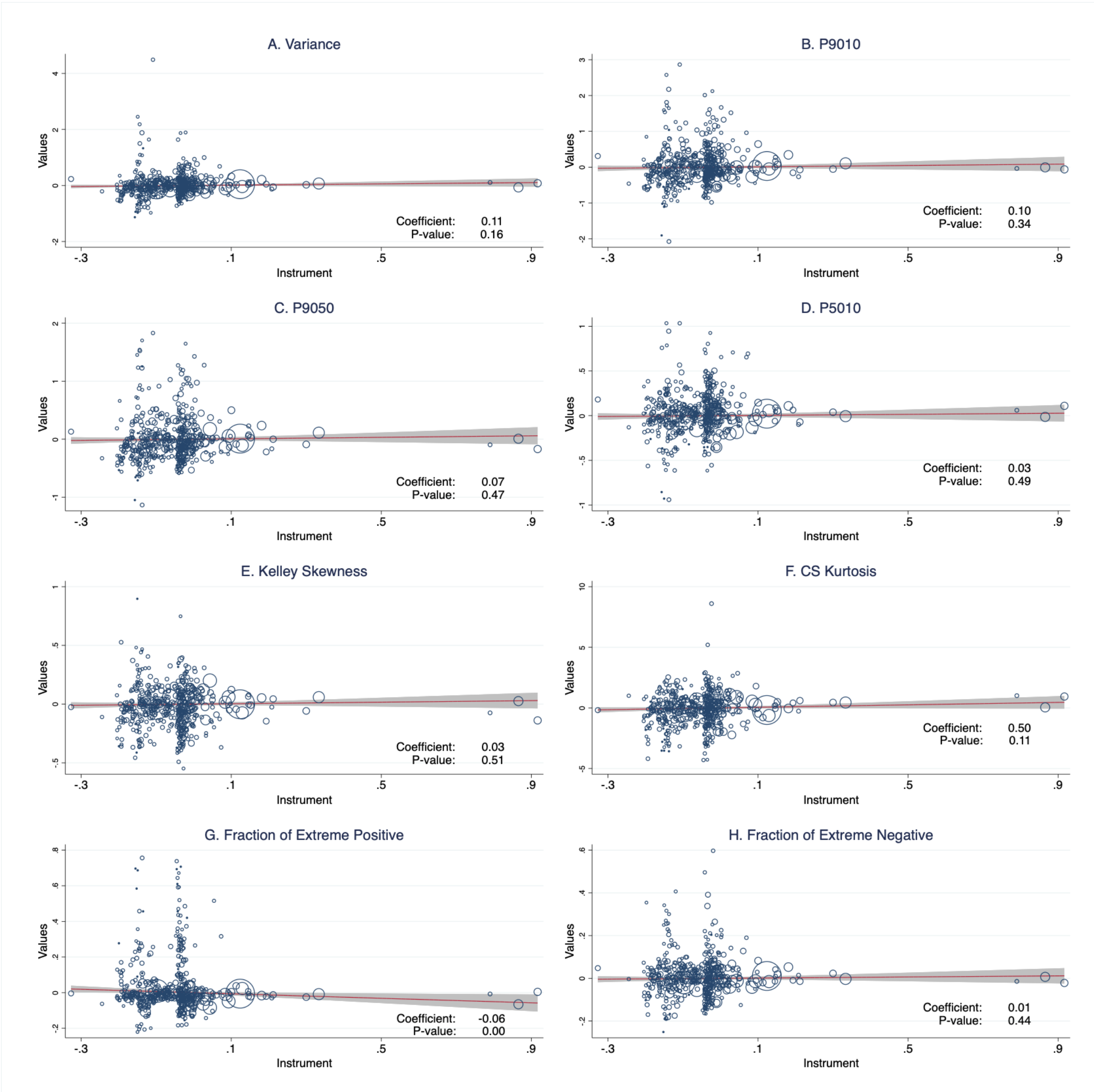
Notes: Panel A plots the share of Chinese participation in the world's merchandise trade, while Panel B plots Chinese net exports (total exports minus total imports) divided by its GDP. Panel C plots the Chinese participation in Brazilian agricultural and extractive trade, while Panel D plots the Chinese 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.

Figure A.3: Relationship between $m[\Delta^1 y_r^i, 1990]$ and $iv\Delta IP_r$



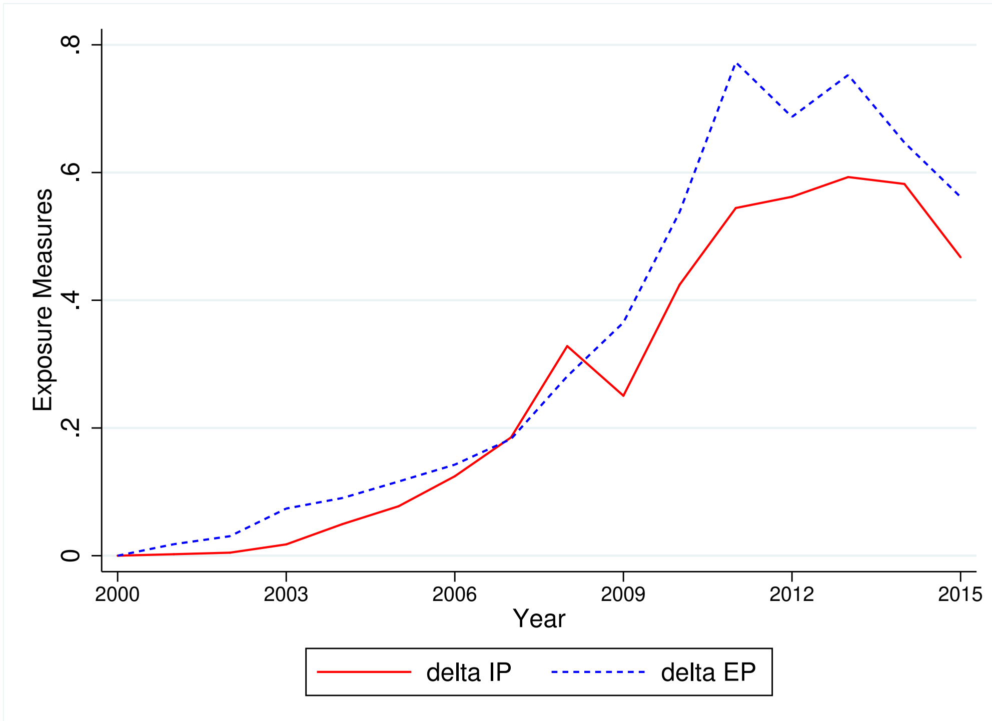
Notes: The figures plot the correlations between the different moments of the distribution of 1-year earnings changes $m[\Delta^1 y_r^i, 1990]$ a decade prior to the China shock and the instrument $iv\Delta IP_r$, conditional only on broad region fixed effects (without additional controls). Coefficients are reported with the respective p-value. Each circle refers to one municipality weighted by its population size in 2000.

Figure A.4: Relationship between $m[\Delta^5 y_r^i, 1990]$ and $iv\Delta IP_r$



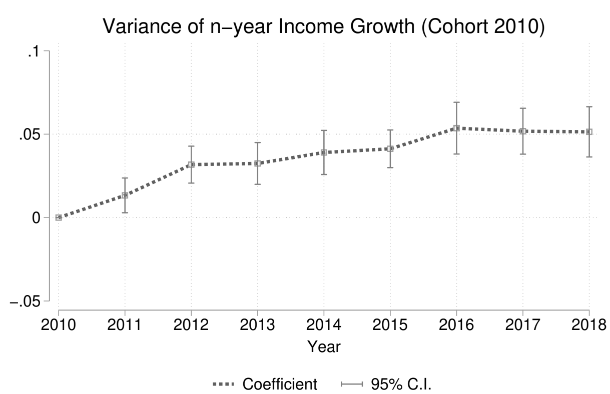
Notes: The figures plot the correlations between the different moments of the distribution of 5-year earnings changes $m[\Delta^5 y_r^i, 1990]$ a decade prior to the China shock and the instrument $iv\Delta IP_r$, conditional only on broad region fixed effects (without additional controls). Coefficients are reported with the respective p-value. Each circle refers to one municipality weighted by its population size in 2000.

Figure A.5: 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 (2) and (B.1).

Figure A.6: Estimated Coefficient for the Variance of n-year (t = 2010)



Notes: The figure plots the impact of import penetration ΔIP_r on the variance of n-year income growth, $V[\Delta^n y^i_{r,2010}]$ from $n = 1$ to $n = 8$. 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.

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

	$m[\Delta^3 y^i_{r,1997}]$			
	Nat.	P25	P50	P75
Dispersion				
Variance	0.505	0.453	0.509	0.559
P9010	1.346	1.273	1.353	1.446
P9050	0.596	0.550	0.587	0.649
P5010	0.749	0.697	0.751	0.833
Asymmetry and Tails				
Kelley Skewness	-0.114	-0.171	-0.134	-0.083
$P(\Delta^n y^i_t > 0.5)$	0.114	0.103	0.111	0.131
$P(\Delta^n y^i_t < -0.5)$	0.152	0.134	0.152	0.166
C.S. Kurtosis	7.473	6.803	7.689	8.281

Notes: Values of $m[\Delta^3 y^i_{r,1997}]$. 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 all workers. Columns P25, P50, and P75 denote the first, second, and third quartile moment values of 509 Brazilian local labor markets. Quartiles are weighted by the local labor workforce.

Table A.2: Moments by Variance Quintile

Variance Quintile	Q1	Q2	Q3	Q4	Q5
			$m[\Delta^1 y^i_{r,1999}]$		
Variance	0.222	0.292	0.315	0.341	0.419
P9010	0.638	0.826	0.853	0.946	1.143
P9050	0.300	0.376	0.391	0.408	0.491
P5010	0.338	0.451	0.461	0.539	0.652
Kelley Skewness	-0.050	-0.089	-0.081	-0.136	-0.140
$P(\Delta^n y^i_t < 0.0)$	0.562	0.579	0.583	0.586	0.552
$P(\Delta^n y^i_t > 0.5)$	0.061	0.077	0.079	0.077	0.097
$P(\Delta^n y^i_t < -0.5)$	0.084	0.097	0.098	0.112	0.131
C.S. Kurtosis	14.796	13.385	13.173	13.173	12.918
			$m[\Delta^5 y^i_{r,1995}]$		
Variance	0.443	0.559	0.612	0.635	0.756
P9010	1.327	1.514	1.615	1.614	1.870
P9050	0.633	0.670	0.726	0.690	0.770
P5010	0.694	0.844	0.889	0.925	1.099
Kelley Skewness	-0.038	-0.115	-0.104	-0.146	-0.176
$P(\Delta^n y^i_t < 0.0)$	0.412	0.402	0.452	0.482	0.417
$P(\Delta^n y^i_t > 0.5)$	0.193	0.195	0.181	0.163	0.226
$P(\Delta^n y^i_t < -0.5)$	0.125	0.147	0.163	0.176	0.197
C.S. Kurtosis	5.640	5.816	5.902	5.811	5.312

Notes: Average values of $m[\Delta^1 y^i_{r,1999}]$ and $m[\Delta^5 y^i_{r,1995}]$ by the Variance Quintile. 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 moments are calculated for 509 Brazilian local labor markets and are weighted by the local labor workforce.

Table A.3: 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.4: 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.5: Robustness of $\Delta IP_{r\tau}$ with different values of τ

	Var	P9010	Skewness	$P(\Delta^n y_t^i > 0.5)$	$P(\Delta^n y_t^i < -0.5)$
Panel A: τ = 2012					
	$m[\Delta^5 y^i_{r,2010}]$				
ΔIP_r	0.032***	0.060***	-0.038**	0.001	0.009**
	(0.005)	(0.013)	(0.015)	(0.003)	(0.004)
	$m[\Delta^3 y^i_{r,2012}]$				
ΔIP_r	0.024***	0.048***	-0.034**	0.001	0.007**
	(0.005)	(0.016)	(0.014)	(0.002)	(0.003)
	$m[\Delta^1 y^i_{r,2014}]$				
ΔIP_r	0.010**	0.033*	-0.026**	0.000	0.004**
	(0.005)	(0.019)	(0.012)	(0.001)	(0.002)
Observations	509	509	509	508	508
1st Stage F-Stat	152.29	148.13	147.85	151.49	152.04
Panel B: τ = 2010					
	$m[\Delta^5 y^i_{r,2010}]$				
ΔIP_r	0.040***	0.075***	-0.047**	0.001	0.012**
	(0.006)	(0.016)	(0.019)	(0.003)	(0.005)
	$m[\Delta^3 y^i_{r,2012}]$				
ΔIP_r	0.029***	0.059***	-0.043**	0.001	0.009**
	(0.006)	(0.020)	(0.018)	(0.003)	(0.004)
	$m[\Delta^1 y^i_{r,2014}]$				
ΔIP_r	0.013**	0.041*	-0.033**	0.001	0.005**
	(0.006)	(0.024)	(0.016)	(0.002)	(0.003)
Observations	509	509	509	508	508
1st Stage F-Stat	135.86	133.15	131.13	135.23	136.35

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 τ equal to 2015 in equation 2. Here, we test whether the results change if we set τ equal to 2012 (Panel A) or 2010 (Panel B), other possible values for the final year of the shock, as seen in Figure A.5. All columns include region controls in 2000, a control for the baseline value of the one-year income growth of the respective moment ($m[\Delta^1 y^i_{r,1999}]$), and dummies for the five Brazilian macro-regions (specification of column (6) of Table 3). 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 A.6: Robustness of $\Delta IP_{r\tau}$ with different values of τ and start year 1999

	Var	P9010	Skewness	$P(\Delta^n y_t^i > 0.5)$	$P(\Delta^n y_t^i < -0.5)$
Panel A: τ *= 2015*					
	$m[\Delta^5 y^i_{r,2010}]$				
ΔIP_r	0.040***	0.070***	-0.043**	0.001	0.009
	(0.005)	(0.014)	(0.017)	(0.003)	(0.006)
	$m[\Delta^1 y^i_{r,2014}]$				
ΔIP_r	0.010**	0.028	-0.035**	-0.000	0.003
	(0.005)	(0.022)	(0.015)	(0.001)	(0.003)
Observations	509	509	509	508	508
1st Stage F-Stat	24.81	24.55	24.58	24.67	24.73
Panel B: τ *= 2012*					
	$m[\Delta^5 y^i_{r,2010}]$				
ΔIP_r	0.030***	0.055***	-0.034**	0.001	0.008*
	(0.004)	(0.012)	(0.013)	(0.003)	(0.004)
	$m[\Delta^1 y^i_{r,2014}]$				
ΔIP_r	0.009**	0.026	-0.025**	0.000	0.003
	(0.004)	(0.017)	(0.012)	(0.001)	(0.002)
Observations	509	509	509	508	508
1st Stage F-Stat	91.69	89.96	91.07	91.23	91.39
Panel C: τ *= 2010*					
	$m[\Delta^5 y^i_{r,2010}]$				
ΔIP_r	0.038***	0.068***	-0.042**	0.001	0.010*
	(0.005)	(0.014)	(0.017)	(0.003)	(0.005)
	$m[\Delta^1 y^i_{r,2014}]$				
ΔIP_r	0.011**	0.032	-0.032**	0.000	0.004
	(0.005)	(0.021)	(0.015)	(0.001)	(0.002)
Observations	509	509	509	508	508
1st Stage F-Stat	89.65	88.94	88.02	89.65	89.90

Notes: Using the IV framework, this table tests the robustness of the $\Delta IP_{r\tau}$ measure. In baseline, we define 2000 as the first year of the China shock and 2015 as the final year (τ=2015 in equation 2). Here, we set 1999 as the first year of the China shock and we vary τ to be 2012 (Panel B) or 2010 (Panel C). All columns include region controls in 2000, a control for the baseline value of the one-year income growth of the respective moment ($m[\Delta^1 y^i_{r,1999}]$), and dummies for the five Brazilian macro-regions (specification of column (6) of Table 3). 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 A.7: Robustness of results with $m[\Delta^5 y^i_{r,1995}]$ as a control instead of $m[\Delta^1 y^i_{r,1999}]$

	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
					$m[\Delta^5 y^i_{r,2010}]$				
ΔIP_r	0.038***	0.063***	-0.001	0.065***	-0.046**	-0.013	0.001	0.011*	0.044
	(0.006)	(0.018)	(0.016)	(0.013)	(0.018)	(0.024)	(0.004)	(0.006)	(0.139)
					$m[\Delta^3 y^i_{r,2012}]$				
ΔIP_r	0.029***	0.044*	-0.004	0.051***	-0.041**	-0.011	0.000	0.008*	-0.028
	(0.006)	(0.022)	(0.015)	(0.017)	(0.018)	(0.020)	(0.003)	(0.004)	(0.175)
					$m[\Delta^1 y^i_{r,2014}]$				
ΔIP_r	0.012**	0.027	-0.003	0.033**	-0.036**	-0.012	0.000	0.004	-0.009
	(0.006)	(0.023)	(0.010)	(0.015)	(0.016)	(0.017)	(0.002)	(0.003)	(0.421)
Observations	509	509	509	509	509	509	508	508	509
1st Stage F-Stat	335.11	333.51	333.56	332.41	330.16	332.70	339.24	334.83	324.69

Notes: Using the IV framework, this table tests the robustness of results with respect to control $m[\Delta^1 y^i_{r,1999}]$. 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 3. In this table, we include as a control $m[\Delta^5 y^i_{r,1995}]$, 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 ($m[\Delta^5 y^i_{r,1995}]$) 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.8: Robustness of results of dispersion to inclusion of State Fixed Effects

Panel A: Baseline - Geographical Region Fixed Effects				
	Variance	P9010	P9050	P5010
	$m[\Delta^5 y^i_{r,2010}]$			
ΔIP_r	0.041***	0.077***	0.006	0.071***
	(0.006)	(0.015)	(0.013)	(0.014)
	$m[\Delta^3 y^i_{r,2012}]$			
ΔIP_r	0.031***	0.059***	0.002	0.055***
	(0.006)	(0.020)	(0.013)	(0.017)
	$m[\Delta^1 y^i_{r,2014}]$			
ΔIP_r	0.013**	0.039*	0.003	0.033**
	(0.006)	(0.023)	(0.009)	(0.015)
Observations	509	509	509	509
1st Stage F-Stat	339.37	331.58	324.62	343.34
Panel B: Robustness - State Fixed Effects				
	Variance	P9010	P9050	P5010
	$m[\Delta^5 y^i_{r,2010}]$			
ΔIP_r	0.047***	0.066***	0.015	0.049***
	(0.011)	(0.020)	(0.011)	(0.012)
	$m[\Delta^3 y^i_{r,2012}]$			
ΔIP_r	0.026***	0.027	0.008	0.018
	(0.008)	(0.017)	(0.009)	(0.015)
	$m[\Delta^1 y^i_{r,2014}]$			
ΔIP_r	0.014*	0.002	-0.008	0.008
	(0.008)	(0.020)	(0.011)	(0.013)
Observations	508	508	508	508
1st Stage F-Stat	193.90	195.69	197.75	194.60

Notes: This table tests the robustness of results with respect to the inclusion of state fixed effects. In our baseline results (Panel A), we include fixed effects at the broad geographical areas: North, Northeast, Central-West, Southeast and South. In Panel B, we include dummies for each of the states of the country instead. The Federal District is coded with Goiás and Roraima with Amazonas so they are not dropped from the analysis, as they include only one microregion. All columns contain, additionally, the full set of region controls in 2000 and a control for the respective moment in year 2000 ($m[\Delta^1 y^i_{r,1999}]$), 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.9: Robustness of results of asymmetry to inclusion of State Fixed Effects

Panel A: Baseline - Geographical Region Fixed Effects				
	Skewness	$P(\Delta^n y_t^i > 0.5)$	$P(\Delta^n y_t^i < -0.5)$	Kurtosis
		$m[\Delta^5 y^i_{r,2015}]$		
ΔIP_r	-0.048**	0.001	0.011**	0.038
	(0.019)	(0.003)	(0.005)	(0.149)
		$m[\Delta^3 y^i_{r,2012}]$		
ΔIP_r	-0.044**	0.000	0.008**	-0.048
	(0.019)	(0.003)	(0.004)	(0.179)
		$m[\Delta^1 y^i_{r,2014}]$		
ΔIP_r	-0.034**	0.000	0.005*	-0.102
	(0.016)	(0.002)	(0.003)	(0.423)
Observations	509	508	508	509
1st Stage F-Stat	340.51	336.35	336.82	332.66
Panel B: Robustness - State Fixed Effects				
	Skewness	$P(\Delta^n y_t^i > 0.5)$	$P(\Delta^n y_t^i < -0.5)$	Kurtosis
		$m[\Delta^5 y^i_{r,2010}]$		
ΔIP_r	-0.017	0.002	0.007	-0.002
	(0.013)	(0.004)	(0.005)	(0.214)
		$m[\Delta^3 y^i_{r,2012}]$		
ΔIP_r	-0.000	-0.002	0.002	0.073
	(0.015)	(0.004)	(0.003)	(0.195)
		$m[\Delta^1 y^i_{r,2014}]$		
ΔIP_r	-0.004	-0.002	0.001	0.719**
	(0.026)	(0.002)	(0.003)	(0.353)
Observations	508	507	507	508
1st Stage F-Stat	196.62	196.95	195.12	194.07

Notes: This table tests the robustness of results with respect to the inclusion of state fixed effects. In our baseline results (Panel A), we include fixed effects at the broad geographical areas: North, Northeast, Central-West, Southeast and South. In Panel B, we include dummies for each of the states of the country instead. The Federal District is coded with Goiás and Roraima with Amazonas so they are not dropped from the analysis, as they include only one microregion. All columns contain, additionally, the full set of region controls in 2000 and a control for the respective moment in year 2000 ($m[\Delta^1 y^i_{r,1999}]$), 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.10: 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) $\mu[\Delta^{5} w^i_{r,2015}]$
ΔIP_r	-0.076***	-0.039***	-0.068***	-0.035***
	(0.024)	(0.006)	(0.021)	(0.007)
Observations	509	509	509	509
1st Stage F-Stat	344.84	344.84	331.07	331.07

Notes: Using the IV framework, this table estimates the impact of import penetration ΔIP_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 so that 2015 is the final year $(n+t)$. All columns include region controls in 2000 (workers employed in the formal sector, the share of workers with high school and less than 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), and dummies for the five Brazilian macro-regions (North, Northeast, Central-West, Southeast and South). Columns (1) and (2) include $\mu[\Delta^5 y^i_{r,1995}]$, a control for the baseline value of the five-year income growth, while columns (3) and (4) include $\mu[\Delta^5 w^i_{r,1995}]$, a control for the baseline value of the five-year wage growth. 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 A.11: Effect of Trade Shock on the Tails of the Distribution of Income Growth: Job, Industry and Region Switchers and Stayers

	Job		Industry		Region	
	Switchers	Stayers	Switchers	Stayers	Switchers	Stayers
	Fraction with $\Delta^5 y_t^i > 0.5$					
ΔIP_r	0.006**	-0.003	0.008***	-0.006**	0.001	-0.000
	(0.002)	(0.002)	(0.002)	(0.003)	(0.005)	(0.003)
Observations	509	509	509	509	509	509
1st Stage F-Stat	320.42	337.88	334.71	337.17	331.86	336.11
	Fraction with $\Delta^5 y_t^i < -0.5$					
ΔIP_r	0.010**	0.001	0.013***	-0.002	0.002	0.010
	(0.004)	(0.001)	(0.004)	(0.003)	(0.005)	(0.009)
Observations	509	509	509	509	509	509
1st Stage F-Stat	336.98	337.21	344.34	336.43	337.76	338.49

Notes: Using the IV framework, this table estimates the impact of import penetration ΔIP_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 2010 and 2015 that are also job/industry/region switcher/stayers. All columns include region controls in 2000, a control for the baseline value of the one-year income growth of the respective moment ($m[\Delta^1 y_{r,1999}^i]$), and dummies for the five Brazilian macro-regions (specification of column (6) of Table 3). 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 A.12: Effect of Trade Shock on Dispersion of Income Growth by Subgroup

	P9050	P5010	P9050	P5010	P9050	P5010
	High-Income		*High-Skill*		*Old*	
ΔIP_r	-0.002	0.078***	0.004	0.084***	0.006	0.061***
	(0.017)	(0.019)	(0.016)	(0.015)	(0.016)	(0.014)
Observations	509	509	509	509	509	509
1st Stage F-Stat	331.40	344.46	339.11	354.97	323.93	348.88
	Low-Income		*Low-Skill*		*Young*	
ΔIP_r	0.011	0.050***	0.003	0.043**	-0.005	0.064***
	(0.013)	(0.014)	(0.014)	(0.019)	(0.012)	(0.014)
Observations	509	509	509	509	509	509
1st Stage F-Stat	330.99	340.60	319.05	340.78	326.51	341.46

Notes: Using the IV framework, this table estimates the impact of import penetration ΔIP_r on the dispersion of five-year income growth. Income growth is calculated so that 2015 is the final year $(n+t)$. All columns include region controls in 2000, a control for the baseline value of the one-year income growth of the respective moment $(m[\Delta^1 y^i_{r,1999}])$, and dummies for the five Brazilian macro-regions (specification of column (6) of Table 3). 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 A.13: Implied Moments of the Stochastic Processes

	High-skill workers			
	pre-China		Counterfactual	
	Permanent (η)	Transitory (ε)	Permanent (η)	Transitory (ε)
Mean (log, $E[x_i]$)	-0.013	-0.057	-0.015	-0.057
Mean (level, $E[\exp(x_i)]$)	1.000	1.000	1.000	1.000
Variance	0.026	0.171	0.031	0.175
Skewness	-0.094	-3.342	-0.433	-3.392
Kurtosis	2.932	13.436	4.404	13.659
	Low-skill workers			
	pre-China		Counterfactual	
	Permanent (η)	Transitory (ε)	Permanent (η)	Transitory (ε)
Mean (log, $E[x_i]$)	-0.011	-0.080	-0.012	-0.092
Mean (level, $E[\exp(x_i)]$)	1.000	1.000	1.000	1.000
Variance	0.022	0.236	0.025	0.280
Skewness	-1.417	-2.558	-1.245	-2.574
Kurtosis	10.743	8.003	8.538	8.170

Notes: Implied moments of the permanent (η) and transitory mixture (ε) for the income process pre-"China" and counterfactual.

Table A.14: Income Process Fit: Data and Model Moments

	High-skill: "pre-China"		High-skill: counterfactual		Low-skill: "pre-China"		Low-skill: counterfactual		
Moment	Data	Model	Data	Model	Data	Model	Data	Model	Weight
				One-year differences					
P9010	0.756	0.719	0.780	0.758	1.087	1.056	1.099	1.049	0.01332
P9010	0.719	0.719	0.743	0.758	1.099	1.056	1.108	1.049	0.01332
P9010	0.694	0.719	0.718	0.758	1.057	1.056	1.053	1.049	0.01332
P9010	0.680	0.719	0.704	0.758	1.017	1.056	1.027	1.049	0.01332
P9010	0.664	0.719	0.688	0.758	1.015	1.056	1.021	1.049	0.01332
P9050	0.355	0.351	0.352	0.344	0.455	0.448	0.452	0.448	0.01332
P9050	0.334	0.351	0.331	0.344	0.467	0.448	0.463	0.448	0.01332
P9050	0.352	0.351	0.349	0.344	0.440	0.448	0.434	0.448	0.01332
P9050	0.304	0.351	0.300	0.344	0.399	0.448	0.399	0.448	0.01332
P9050	0.340	0.351	0.336	0.344	0.449	0.448	0.444	0.448	0.01332
P5010	0.401	0.368	0.428	0.414	0.632	0.608	0.646	0.602	0.01332
P5010	0.385	0.368	0.413	0.414	0.633	0.608	0.645	0.602	0.01332
P5010	0.341	0.368	0.369	0.414	0.617	0.608	0.619	0.602	0.01332
P5010	0.376	0.368	0.403	0.414	0.617	0.608	0.627	0.602	0.01332
P5010	0.324	0.368	0.351	0.414	0.566	0.608	0.577	0.602	0.01332
C.S. Kurtosis	8.579	10.997	8.515	10.912	10.030	11.981	9.890	11.709	0.01332
C.S. Kurtosis	10.521	10.997	10.457	10.912	11.961	11.981	11.809	11.709	0.01332
C.S. Kurtosis	10.405	10.997	10.340	10.912	12.413	11.981	12.293	11.709	0.01332
C.S. Kurtosis	12.941	10.997	12.876	10.912	13.930	11.981	13.799	11.709	0.01332
C.S. Kurtosis	11.459	10.997	11.395	10.912	14.408	11.981	14.267	11.709	0.01332
Share <-0.5	0.077	0.086	0.081	0.084	0.110	0.109	0.111	0.111	0.00666
Share <-0.5	0.079	0.086	0.083	0.084	0.113	0.109	0.114	0.111	0.00666
Share <-0.5	0.076	0.086	0.079	0.084	0.116	0.109	0.116	0.111	0.00666
Share <-0.5	0.079	0.086	0.083	0.084	0.113	0.109	0.114	0.111	0.00666
Share <-0.5	0.075	0.086	0.078	0.084	0.110	0.109	0.111	0.111	0.00666
Share > 0.5	0.075	0.086	0.075	0.073	0.105	0.097	0.105	0.096	0.00666
Share > 0.5	0.068	0.086	0.068	0.073	0.103	0.097	0.103	0.096	0.00666
Share > 0.5	0.066	0.086	0.066	0.073	0.091	0.097	0.090	0.096	0.00666
Share > 0.5	0.062	0.086	0.062	0.073	0.088	0.097	0.088	0.096	0.00666
Share > 0.5	0.063	0.086	0.063	0.073	0.090	0.097	0.089	0.096	0.00666
				Three-year differences					
P9010	1.150	1.136	1.180	1.156	1.459	1.455	1.461	1.430	0.0222
P9010	1.145	1.136	1.175	1.156	1.482	1.455	1.485	1.430	0.0222
P9010	1.136	1.136	1.166	1.156	1.448	1.455	1.449	1.430	0.0222
P9050	0.554	0.555	0.548	0.538	0.637	0.622	0.624	0.608	0.0222
P9050	0.545	0.555	0.540	0.538	0.639	0.622	0.631	0.608	0.0222
P9050	0.554	0.555	0.549	0.538	0.615	0.622	0.604	0.608	0.0222
P5010	0.597	0.581	0.632	0.617	0.822	0.834	0.836	0.822	0.0222
P5010	0.600	0.581	0.635	0.617	0.843	0.834	0.853	0.822	0.0222
P5010	0.583	0.581	0.618	0.617	0.833	0.834	0.844	0.822	0.0222
C.S. Kurtosis	6.142	6.695	6.167	6.784	6.992	8.284	6.790	8.008	0.0222
C.S. Kurtosis	7.249	6.695	7.274	6.784	7.521	8.284	7.415	8.008	0.0222
C.S. Kurtosis	7.184	6.695	7.209	6.784	7.837	8.284	7.728	8.008	0.0222
Share <-0.5	0.104	0.129	0.109	0.141	0.130	0.145	0.131	0.153	0.0111
Share <-0.5	0.108	0.129	0.113	0.141	0.139	0.145	0.138	0.153	0.0111
Share <-0.5	0.111	0.129	0.116	0.141	0.147	0.145	0.148	0.153	0.0111
Share > 0.5	0.140	0.105	0.140	0.103	0.176	0.113	0.174	0.114	0.0111
Share > 0.5	0.127	0.105	0.126	0.103	0.160	0.113	0.158	0.114	0.0111
Share > 0.5	0.119	0.105	0.119	0.103	0.138	0.113	0.136	0.114	0.0111
				Five-year differences					
P9010	1.375	1.380	1.416	1.417	1.644	1.661	1.660	1.701	0.0668
P9050	0.653	0.681	0.654	0.668	0.696	0.709	0.688	0.722	0.0668
P5010	0.722	0.699	0.762	0.749	0.948	0.952	0.970	0.979	0.0668
C.S. Kurtosis	5.568	5.362	5.514	5.379	5.994	6.510	6.011	6.452	0.0668
Share <-0.5	0.121	0.177	0.128	0.191	0.146	0.176	0.149	0.190	0.0334
Share > 0.5	0.185	0.132	0.186	0.129	0.217	0.128	0.216	0.132	0.0334
Loss function		0.009150		0.009265		0.007220		0.007952	

B Export Penetration

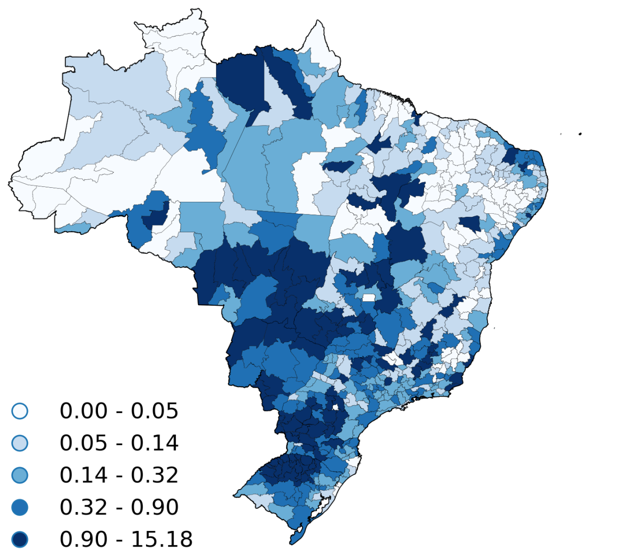
As discussed in Section 2.3, the *China rise* also caused positive export demand shocks in Brazil and in other commodities-based economies. Indeed, using data from the Brazilian Census containing formal and informal workers, Costa et al. (2016) found that the export demand shock induced by the Chinese 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 (ΔEP_r) on income risk is, however, unclear. As explained in Section 2.3, 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 in the short run. Moreover, and most importantly, the export penetration shock is largely concentrated in the agricultural and extractive sectors, as shown in Panel C of Figure A.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 2 for ΔIP_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 ΔV_{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 (2). Figure B.1 shows the spatial distribution of ΔEP_r across Brazilian local labor markets. Differently from the ΔIP_r shown in Figure 1, which was mostly concentrated in the highly industrialized and most populated areas in the South and Southeast regions of Brazil, the ΔEP_r shock is more widespread across the Brazilian territory and mostly localized in the agricultural areas of the Central-West and the South and in smaller areas of the North and the Northeast. Importantly for our identification purposes, the raw correlation between the ΔIP_r and ΔEP_r variable is -6% (population-weighted), although not statistically different from zero. Therefore, although the impact of the ΔEP_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 (ΔEP_r)



Notes: The figure plots the distribution of variable ΔEP_r across Brazilian local labor markets. ΔEP_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 presents results of our regressions estimating the impact of ΔEP_r, where we instrument ΔEP_r by $iv\Delta EP_r$, defined analogously to equation (5). In Panel B, then, we include ΔIP_r and ΔEP_r simultaneously. Table B.1 shows that the impact of ΔEP_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 ΔIP_r shock increases risk at the bottom of the income distribution (P5010) and its effect is much larger than the effect of ΔEP_r.

Table B.2 shows that the impact of ΔEP_r on asymmetry and tails of the distribution is also small. An increase in ΔEP_r of \$1000 per worker reduces the share accounted by the P9050 in the P9010 distribution in 0.15, 0.5, and 0.75 p.p. for the five, three, and one-year income growth distribution respectively. The analogous results for the ΔIP_r shock shown in Table B.2 were more significant: 2.4, 2.2 and 1.7 p.p. 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 estimates are not precisely estimated.

Finally, Table B.3 shows that the impact of ΔEP_r on the growth of labor income of hourly wages is close to zero and insignificant.

In sum, results from B.1, B.2 and B.3 show that, although the results induced by the ΔEP_r occur mostly in reasonable directions, they are expressively smaller in magnitude than the ones induced by the ΔIP_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 ΔIP_r. Importantly, however, we show that the existence of the ΔEP_r shock in Brazil does not affect our estimates for the coefficients of ΔIP_r.

Table B.1: Effect of ΔEP_r on Dispersion of Income Growth

	Variance	P9010	P9050	P5010
Panel A: Only Export Penetration				
	$m[\Delta^5 y^i_{r,2010}]$			
ΔEP_r	0.002	0.004	-0.002	0.005
	(0.003)	(0.005)	(0.003)	(0.003)
	$m[\Delta^3 y^i_{r,2012}]$			
ΔEP_r	0.000	0.000	-0.008***	0.008**
	(0.002)	(0.004)	(0.002)	(0.003)
	$m[\Delta^1 y^i_{r,2014}]$			
ΔEP_r	0.001	0.003	-0.008***	0.010**
	(0.002)	(0.005)	(0.003)	(0.004)
Observations	509	509	509	509
1st Stage F-Stat	19.29	19.23	19.30	19.06
Panel B: Import and Export Penetration				
	Variance	P9010	P9050	P5010
	$m[\Delta^5 y^i_{r,2010}]$			
ΔIP_r	0.041***	0.076***	0.007	0.070***
	(0.006)	(0.016)	(0.013)	(0.014)
ΔEP_r	0.001	0.002	-0.002	0.003
	(0.003)	(0.005)	(0.003)	(0.003)
	$m[\Delta^3 y^i_{r,2012}]$			
ΔIP_r	0.031***	0.059***	0.004	0.054***
	(0.006)	(0.020)	(0.013)	(0.017)
ΔEP_r	-0.001	-0.001	-0.008***	0.006*
	(0.002)	(0.004)	(0.002)	(0.004)
	$m[\Delta^1 y^i_{r,2014}]$			
ΔIP_r	0.012**	0.038*	0.005	0.030*
	(0.006)	(0.023)	(0.009)	(0.016)
ΔEP_r	0.001	0.002	-0.008***	0.009**
	(0.002)	(0.005)	(0.003)	(0.004)
Observations	509	509	509	509
1st Stage F-Stat	10.03	9.97	10.01	9.92

Notes: Using the IV framework, this table estimates the impact of export ΔEP_r and import penetration ΔIP_r on the dispersion of five ($\Delta^5 y^i_{r,2010}$), three ($\Delta^3 y^i_{r,2012}$) and one-year ($\Delta^1 y^i_{r,2011}$) income growth. Income growth is calculated so that 2015 is the final year. All columns include region controls in 2000, a control for the baseline value of the one-year income growth of the respective moment ($m[\Delta^1 y^i_{r,1999}]$), and dummies for the five Brazilian macro-regions (specification of column (6) of Table 3). 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 ΔEP_r 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
Panel A: Only Export Penetration				
	$m[\Delta^5 y^i_{r,2010}]$			
ΔEP_r	-0.003	0.000	-0.001	-0.003
	(0.003)	(0.001)	(0.001)	(0.019)
	$m[\Delta^3 y^i_{r,2012}]$			
ΔEP_r	-0.010***	-0.001	-0.000	-0.034
	(0.003)	(0.001)	(0.001)	(0.033)
	$m[\Delta^1 y^i_{r,2014}]$			
ΔEP_r	-0.015***	-0.001**	0.001	-0.155*
	(0.004)	(0.000)	(0.001)	(0.085)
Observations	509	508	508	509
1st Stage F-Stat	19.15	19.46	19.19	19.18
Panel B: Import and Export Penetration				
	Skewness	$P(\Delta^n y_t^i > 0.5)$	$P(\Delta^n y_t^i < -0.5)$	Kurtosis
	$m[\Delta^5 y^i_{r,2010}]$			
ΔIP_r	-0.048**	0.001	0.012**	0.039
	(0.019)	(0.004)	(0.005)	(0.150)
ΔEP_r	-0.002	0.000	-0.001	-0.004
	(0.003)	(0.001)	(0.001)	(0.019)
	$m[\Delta^3 y^i_{r,2012}]$			
ΔIP_r	-0.041**	0.001	0.008**	-0.038
	(0.019)	(0.003)	(0.004)	(0.183)
ΔEP_r	-0.009***	-0.001	-0.000	-0.034
	(0.003)	(0.001)	(0.001)	(0.034)
	$m[\Delta^1 y^i_{r,2014}]$			
ΔIP_r	-0.030*	0.001	0.004*	-0.055
	(0.015)	(0.002)	(0.003)	(0.421)
ΔEP_r	-0.015***	-0.001**	0.001	-0.154*
	(0.004)	(0.001)	(0.001)	(0.083)
Observations	509	508	508	509
1st Stage F-Stat	9.96	10.09	9.96	9.97

Notes: Using the IV framework, this table estimates the impact of export ΔEP_r and import penetration ΔIP_r on the asymmetry and tails of the income growth distribution. Income growth is calculated so that 2015 is the final year. Skewness refers to the Kelley skewness and kurtosis refers to Crow-Siddiqui kurtosis. All columns include region controls in 2000, a control for the baseline value of the one-year income growth of the respective moment ($m[\Delta^1 y^i_{r,1999}]$), and dummies for the five Brazilian macro-regions (specification of column (6) of Table 3). 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 ΔEP_r on Mean of Log of Labor Income Growth and Log of Hourly Wages Growth

Panel A: Only Export Penetration				
	(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) $\mu[\Delta^{5}w^i_{r,2015}]$
ΔEP_r	0.003	-0.000	0.005	0.002
	(0.005)	(0.002)	(0.005)	(0.002)
Observations	509	509	509	509
1st Stage F-Stat	19.20	19.20	19.22	19.22

Panel B: Import and Export Penetration				
	(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) $\mu[\Delta^{5}w^i_{r,2015}]$
ΔIP_r	-0.077***	-0.039***	-0.070***	-0.036***
	(0.024)	(0.006)	(0.021)	(0.007)
ΔEP_r	0.005	0.001	0.007	0.003
	(0.005)	(0.002)	(0.005)	(0.002)
Observations	509	509	509	509
1st Stage F-Stat	9.93	9.93	9.99	9.99

Notes: Using the IV framework, this table estimates the impact of export ΔEP_r and import penetration ΔIP_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 so that 2015 is the final year. All columns include region controls in 2000 (workers employed in the formal sector, the share of workers with high school and less than 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 five-year income/wage growth respective moment ($m[\Delta^1 y^i_{r,1995}]$) and dummies for the five Brazilian Macro-regions (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.

C 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 stochastic income process. It accounts for time-varying and region-specific distributions of idiosyncratic shocks. Let $y^i_{r,t}$ be the log yearly earnings of a worker i at year t in the local labor market r:

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

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 permanent component, $z^i_{r,t}$, modeled as a unit root with iid innovations η^i_t drawn from a distribution F_η, and an iid transitory innovation ε^i_t, drawn from a distribution F_ε. 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 $\varepsilon^i_{r,t}$. By increasing the dispersion (and possibly higher moments) of F_η and F_ε, 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_ε and F_η.

Given the stochastic process specified in Equation (C.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 consider only workers who have not moved out of their original labor market.[37] Then, define the income growth from t to $t+n$

[37] Including movers substantially complicates the analysis of the stochastic process as we must keep track of the entire location history of the workers, and the number of possible histories increases exponentially and the number of possible histories increases with larger time horizons. In the main analysis, we include both movers and non-movers. As movers are a small fraction of the workers in a local labor market, the main intuition remains.

of an individual in region r as $\Delta^n y^i_{r,t} = y^i_{r,t+n} - y^i_{r,t}$ and re-write it as:

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

We can write the variance of the distribution of $n-$year earnings in year t and labor market r, $\sigma^2(\Delta^n y_{r,t})$, as a function of the variances of F_η and F_ϵ:

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

Equation (C.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_η and F_ε, 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 $\Delta^n y^i_{r,t}$, this is evidence that the local labor market shock has an impact in the persistent idiosyncratic risk.

C.1 Higher Moments of the Income Process

We can extend the previous analysis to higher moments, and show that the $n-$year distribution of earnings change is informative about the higher moments of the stochastic process. Let us denote $k^j(x(t))$ as the j_{th} cumulant of the distribution $F_x(t)$.[38] Then, applying the properties of the cumulants it is easy to see that:

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

[38]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 $k^4(x) = \mu^4(x) - 3[\mu^2(x)]^2$.

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

$$\sigma^2(\Delta^n y_{r,t}) = \sum_{k=1}^{n} \sigma_\eta^2(r,t+k) + \sigma_\epsilon^2(r,t+n) + \sigma_\epsilon^2(r,t), \tag{C.5}$$

$$\mathcal{S}(\Delta^n y_{r,t}^i) = \sum_{k=1}^{n} \mathcal{S}_\eta(r,t+k) + \mathcal{S}_\varepsilon(r,t+n) - \mathcal{S}_\varepsilon(r,t), \tag{C.6}$$

$$\begin{aligned}\mathcal{K}(\Delta^n y_{r,t}^i) - 3\sigma^4(\Delta^n y_{r,t}^i) &= \sum_{k=1}^{n} [\mathcal{K}_\eta(r,t+k) - 3\sigma_\eta^4(r,t+k)] + ... \\ &... + [\mathcal{K}_\varepsilon(r,t+n) - 3\sigma_\varepsilon^4(r,t+n)] + [\mathcal{K}_\varepsilon(r,t) - 3\sigma_\varepsilon^4(r,t))].\end{aligned} \tag{C.7}$$

D Estimation of the Income Process

We estimate two stochastic income processes for both high and low-skill workers. The first income process is estimated by targeting empirical moments of the distribution of income growth using the nationwide sample of 1,000,000 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 ΔIP_r and ΔEP_r times the estimated coefficients of the empirical sections. The (weighted) average increase of ΔIP_r (0.467) and ΔEP_r (0.564) times the estimated coefficients taken, for instance, from Table A.12.[39]

The estimated income process is given by:

$$y_t^i = z_t^i + \varepsilon_t^i \tag{D.1}$$

$$z_t^i = z_{t-1}^i + \eta_t^i \tag{D.2}$$

$$\eta_t^i \sim \begin{cases} N(\mu_{\eta,1}, \sigma_{\eta,1}^2) & \text{with prob. } p_\eta \\ N(\mu_{\eta,2}, \sigma_{\eta,2}^2) & \text{with prob. } 1 - p_\eta \end{cases} \tag{D.3}$$

$$\varepsilon_t^i \sim \begin{cases} N(\mu_{\varepsilon,1}, \sigma_{\varepsilon,1}^2) & \text{with prob. } p_\varepsilon \\ N(\mu_{\varepsilon,2}, \sigma_{\varepsilon,2}^2) & \text{with prob. } 1 - p_\varepsilon \end{cases} \tag{D.4}$$

We restrict the mean in levels of both the persistent and transitory innovations to unity: $\mathbb{E}[\exp\{\eta_t^i\}] = 1$ and $\mathbb{E}[\exp\{\varepsilon_t^i\}] = 1$.[40] 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 $\mathbb{E}[\exp\{\eta_t^i\}] = 1$ and $\mathbb{E}[\exp\{\varepsilon_t^i\}] = 1$ respectively. We carry on the estimation using the Simulated Method of Moments. Particularly, we target the $P9010$, $P9050$, $P5010$, the share of log changes of more than 0.5, $P(\Delta^n y_i > 0.5)$, and less than -0.5, $P(\Delta^n y_i < -0.5)$, 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 log changes higher than 0.5 and for the share of log changes lower than -0.5. 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 distribution. We re-weight

[39] For example, the $P9010[\Delta^5 y_{1995}^i]$ of high-skill workers is equal to 1.375. The post-China counterfactual P9010 is calculated as $P9010[\Delta^5 y_{CF}^i] = 1.375 + 0.467 \times 0.0853 + 0.562 \times 0.0011 = 1.415$, where 0.467 and 0.564 are the average increase of ΔIP_r and ΔEP_r. In practice, most of the coefficients of ΔEP_r are an order of magnitude smaller than the ones from ΔIP_r, and therefore are irrelevant for the estimation.

[40] Note that this can be done in close form. For a random variable, x^i, that follows a mixture of normal distributions, the mean is given by: $\mathbb{E}[\exp\{x^i\}] = p \exp\{\mu_1 + \sigma_1^2/2\} + (1-p)\exp\{\mu_2 + \sigma_2^2/2\} = 1$.

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 93,000 income histories using the stochastic process above 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:

$$F_j(\Theta) = \frac{\hat{k}_j(\Theta) - \hat{k}_{j,N}}{|\hat{k}_{j,N}|}. \tag{D.5}$$

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

$$\hat{\Theta} = \text{argmin}_{\Theta} F(\Theta)' W F(\Theta). \tag{D.6}$$

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. (2021). In the first stage of the algorithm, we randomly evaluate 10,000 initial parameter vectors (chosen based on a Sobol sequence). Afterward, based on the loss function, the 5% best guesses are selected and carried out 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 D.6. We compute standard errors using block bootstrap at the individual level (300 replications). The model fit is in Table A.14.

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.4. 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:

$$k^j(\Delta y^i_{t+1}) + k^j(\Delta y^i_t) - k^j(\Delta^2 y^i_{t+1}) = 2k^j(\varepsilon^i_t) \tag{D.7}$$

$$k^j(\Delta^2 y^i_{t+1}) + k^j(\Delta^2 y^i_t) - k^j(\Delta y^i_{t+1}) - k^j(\Delta y^i_{t-1}) = 2k^j(\eta^i_t). \tag{D.8}$$

Where k^j is the j_{th} cumulant. Intuitively this approach is similar to using 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 implicitly 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 the 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.

E Model

E.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 includes an income floor calibrated as the unemployment benefit of a worker who earns the minimum wage. It is defined as follows:

1. First, we apply the income floor, $\underline{u}$: $\underline{w}_t^i = \max\{w_t^i, \underline{u}\}$, where $\underline{u} = 1305.60$.

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

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

3. 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 individual's last realization bounded by a minimum and a maximum value (except in the counterfactuals, where the replacement rate is chosen to maintain the average pension rate constant):[41]

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

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