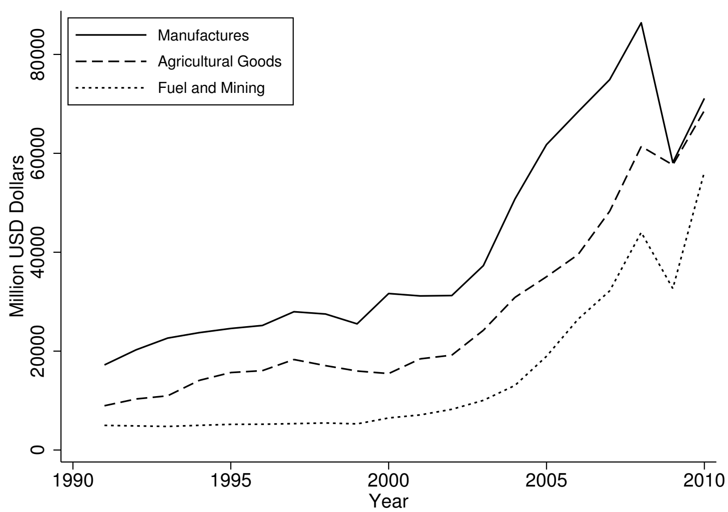
Appendix for Online Publication

A The Brazilian Economy

A.1 Brazilian Trade Patterns

Brazil was a relatively closed economy to international trade up to the late 1980s. In the 1990s, with reductions in import tariffs and the Mercosur Trade Agreement, Brazil started to open to international trade. After 1999, exports increased substantially after a large-scale devaluation and changes to the exchange rate regime. Exports further accelerated after 2002, following another depreciation episode and an improvement in international agricultural prices. Table A.1 shows exports for manufactured goods, agricultural goods, and fuel over our sample period. There was a sharp increase in exports after 2000, and manufactures represented a large share of Brazil's exports.

Figure A.1: Brazil's Exports in 1990–2010



Notes: The data comes from the WTO. This graph shows the value of exports in millions of dollars for manufacturing goods, agricultural goods, and fuels and mining products in the period 1990–2010.

Rocha et al. (2008) document the diversification of Brazil's exports across a variety of products. Apart from agricultural merchandize, Brazil intensively exports chemicals, pharmaceutical products, aircraft, automobiles, and home appliances. In 2004, more than 15,000 Brazilian firms exported more than 10,000 8-digit HS products.

Table A.1 presents the share of Brazil's exports by destination. In the 1990s, thanks to the Mercosur agreement, there was an increase in the share of exports to Argentina, whose share in Brazil's exports increased from 2% in 1990 to 11% in 2000. While the United States remained the largest foreign market for Brazilian exporters in 1990 with 25% of total exports, the share decreased to 10% in 2010. Between 1990 and 2010, the share of exports destined to East Asia and the Pacific increased, mostly explained by the increase in exports going to China (1% in 1990 to 15% in 2010). The main takeaway is that Brazil exports to a wide variety of destinations with

Table A.1: Share of Exports (%) by Trading Partners

	1990	2000	2010		1990	2000	2010
By Region				*By Country (Top 15)*			
Europe & Central Asia	31.93	30.78	25.63	China	1.22	1.97	15.25
East Asia & Pacific	15.34	10.93	25.11	United States	24.62	24.29	9.64
Latin America & Caribbean	11.67	24.99	23.26	Argentina	2.05	11.32	9.17
United States	24.62	24.29	9.64	Netherlands	7.94	5.07	5.07
Middle East & North Africa	0	3.35	7.33	Germany	5.69	4.58	4.03
Sub-Saharan Africa	1.91	1.52	2.49	Japan	7.48	4.49	3.54
				United Kingdom	3.01	2.72	2.3
				Chile	1.54	2.26	2.11
				Italy	5.14	3.89	2.1
				Russian Federation	0	0.77	2.06
				Spain	2.24	1.83	1.93
				Venezuela	0.85	1.37	1.91
				Korea, Rep.	1.73	1.05	1.86
				Mexico	1.61	3.11	1.84
				France	2.87	3.25	1.79

Notes: This table presents the share of exports to each destination market. The data is collected from the WITS (the World Integrated Trade Solution). The countries and regions are ranked by the share of exports in 2010.

around half of total exports going to high-income economies (including the United State, the Euro area and Japan) and half going to other developing countries.

Table A.2 presents the share of total exports, the value, and the revealed comparative advantage index for main products Brazil exported in the years 1990 and 2010. 22% of Brazil's exports in 1990 and 42% in 2010 were raw materials. This means that around 80% (60%) of its exports were manufactured goods in 1990 (2010). Moreover, although the share of raw materials in total exports increased in this period, it is worth noting that the export value of manufactured products also substantially increased.

A.2 Brazilian Economic Background and Informality

One caveat of the analysis is that RAIS misses the informal firms. Here we provide a discussion on the economic and political background of the Brazilian informal labor market. Because of the economic instability and high unemployment rates due to the recession, the share of unregistered employees (informal workers) in total employees grew from 1990 to 2003. After 2002, an economic expansion went along with improvements in socio-economic outcomes and a considerable decrease in unemployment and unregistered workers. For an extensive review of policies and the informal sector in Brazil see Dix-Carneiro et al. (2021).

Figure A.2a shows unregistered workers as a share of total employees. The informality rate sharply declined in recent decades, from around 33% in the 1990s to 23% in the 2010s. In Brazil's Population Census 2000 and 2010, we have information on the contract status of wage workers. We split the sample into wage workers with formal contracts and with no formal contracts. Data is only available for two years, so we are not able to apply the HLT method. To provide a reference, we draw the experience-wage profiles in the cross section. Figure A.3a plots both profiles and

Table A.2: Exports by Products

	Product Share (%)		Value (U.S.$ Mill)		RCAI	
	1990	2010	1990	2010	1990	2010
By Type						
Raw materials	21.37	41.93	6,713	84,671	1.84	2.93
Intermediate goods	39.01	27.29	12,252	55,109	1.75	1.28
Consumer goods	20.81	14.62	6,537	29,517	0.56	0.44
Capital goods	15.45	14.27	4,854	28,822	0.35	0.42
By Product						
Minerals	8.93	15.63	2,804	31,557	10.26	10.79
Food Products	16.83	13.4	5,287	27,056	4.46	4.21
Vegetable	9.02	10.88	2,831	21,961	2.61	3.81
Fuels	2.17	9.83	682	19,843	0.03	0.61
Transportation	7.32	8.55	2,299	17,272	0.35	0.88
Mach and Elec	11.17	8.03	3,509	16,216	0.32	0.28
Metals	17.17	7.14	5,393	14,412	2.89	0.9
Animal	2.07	6.7	650	13,526	0.8	3.46
Chemicals	4.89	5.06	1,535	10,221	0.62	0.57
Wood	5.28	4.33	1,659	8,740	0.95	2.11
Miscellaneous	2.43	2.98	762	6,023	0.17	0.33
Plastic or Rubber	2.56	2.65	804	5,341	0.5	0.57
Stone and Glass	1.37	1.96	431	3,954	0.56	0.36
Textiles and Clothing	3.97	1.12	1,248	2,265	0.67	0.28
Hides and Skins	1.03	0.92	323	1,865	1.62	1.5
Footwear	3.78	0.82	1,188	1,653	1.95	1.07

Notes: This table presents the share of exports in Columns 1–2, the value of exports in Columns 3–4, and the revealed comparative advantage indices in Columns 5–6 for the years 1990 and 2010. The data is collected from WITS (World Integrated Trade Solution). The products and products types are ranked by the share of exports in 2010.

shows that formal workers have steeper experience-wage profiles than informal workers.

In addition to informal employment, three further types of work are not reported in RAIS: self-employed workers, owner-managers who do not pay themselves a wage under Brazilian tax incentives, and unpaid workers because RAIS only reports work if it generates a formal wage payment. Figure A.2b shows the share of self-employed workers, employers and unpaid workers in Brazilian total employment. These three types of employment represented 30–40% of Brazilian employment in the 1990s and 2000s. We use the Brazilian Population Census in 1991, 2000, and 2010 to compare experience-wage profiles for Brazilian wage workers and self-employed workers. We estimate experience-wage profiles by applying the HLT method. Differing from the Mincer regressions estimated in Section II.B, because we cannot identify the same individuals in multiple rounds of the Brazilian Population Census, we do not use the individual-level wage growth (we instead control for cohort effects of birth years). We apply the identical Mincer regression of wage levels as in Lagakos et al. (2018), with 10 years of no experience returns at the end of the working life and a 0% depreciation rate. As shown in Figure A.3b, we find that wage workers have steeper profiles than self-employed workers.

Dix-Carneiro et al. (2021) show that within tradable sectors, most workers are formally em-

(a) Share of Informal Employees

(b) Share of Non-employees in Occupied Pop

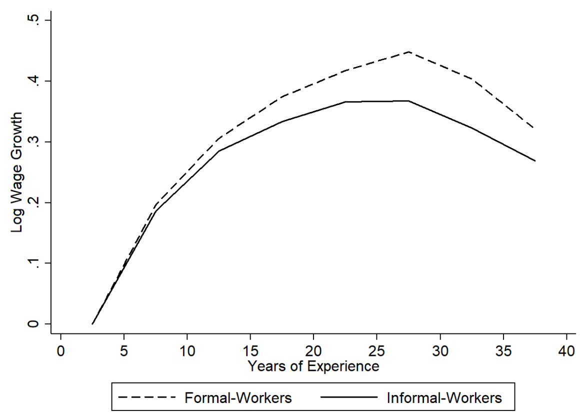
Notes: The left-hand figure shows the share of unregistered employees in total employees. In the right-hand panel, the share of self-employed people represents the ratio of the amount of self-employed workers to total occupied population. The share "+ employers" is the share of self-employed and employers in total occupied population. The share "+ Unpaid" is the share of self-employed, employers, and unpaid workers in total occupied population. The data comes from the PNAD censuses.

ployed. Moreover, they show that the transition between formality and informality is relatively low. Therefore, given our focus on tradable industries, informality should not be a big issue. Nevertheless, even considering informal workers, because exporters are mostly formal firms, it is likely that non-exporters hire informal workers more intensively than exporters. By missing informal workers, we may underestimate the difference in experience-wage profiles between exporters and non-exporters and the benefits of trade in inducing workers' transition from informal to formal firms in our main results.

B Description of the RAIS and Customs Data

We use the Brazilian employer-employee data named RAIS (Relacao Anual de Informacoes Sociais). Plant-level information in RAIS is based on the CNPJ identification number, where CNPJ ("cadastro nacional de pessoa juridica") stands for Brazil's national register of legal entities. The first eight digits of CNPJ numbers (CNPJ radical) define the firm and the subsequent six digits the plant within the firm. The CNPJ number is assigned or extinguished, and pertaining register information updated, under legally precisely defined conditions (Muendler et al., 2012). We focus on firms and aggregate establishments into the affiliated firms, because our export destination data is only available for firms. As discussed in Muendler et al. (2012), a firm's identification code may change in the following situations: (1) when the firm is opened, it is required to register a code with the federal tax authorities upon opening a business; (2) in the case of mergers and complete divestitures, the newly independent firm obtains a own registration code; (3) in the case of an acquisition, the acquiring firm's code is retained, whereas the acquired firm's code will be extinguished; and (4) when the firm exits, the code will be extinguished. In the paper, we refer to firms' identification codes as firm IDs and rely on firm IDs to identify and track firms.

Firms are mandated by law to annually provide workers' information to RAIS, and thus the data



(a) Informal and Formal Workers

(b) Wage and Self-employed Workers

Notes: The left-hand figure shows experience-wage profiles separately for male wage workers with and without formal contracts. We rely on Brazilian Census data available in IPUMS for the years 2000 and 2010. The right-hand figure shows experience-wage profiles separately for male wage workers and male self-employed workers, derived from the HLT method (identical regression as in Lagakos et al. (2018)). We rely on Brazilian Census data available in IPUMS for the years 1991, 2000, and 2010.

contains annual information on most workers employed in the Brazilian formal sector.[1] The data is available from 1986. Nonetheless, the detailed data on age and hours worked is only available after 1994, and these two variables are important to accurately measure experience-wage profiles.

The occupation classification in RAIS is based on the CBO (Classificação Brasileira de Ocupações), which has more than 350 categories and can be aggregated to 5 broad occupations (professionals, technical workers, other white-collar workers, skilled blue-collar workers, and unskilled blue-collar workers). The industry classification is based on the CNAE (Classificação Nacional de Atividade Econômica), which has 564 5-digit industries. Although there is available data on agriculture and services, we only focus on manufacturing industries, as manufacturing firms are tradable and extensively studied in the literature. The data contains monthly average wage and wages of December, which are measured by multiples of the contemporaneous minimum wage. We follow Menezes-Filho, Muendler and Ramey (2008) to transform these earnings into the Brazilian Real and deflate them to the August 1994 price level. For the cases with more than one observations per worker-year, we keep the observation with the highest hourly wage (Dix-Carneiro, 2014). Most workers are employed only at one firm in a year, and the average number of observations per worker-year is roughly 1.1.

We use firm IDs (8-digit identification codes) to merge the RAIS data with Brazilian customs declarations for merchandise exports collected at SECEX (Secretaria de Comércio Exterior) for the years 1994–2010.[2] Thus, we use RAIS merged with customs data for the 1994–2010 period. From Brazilian customs declarations, we have data on destination markets for all firms in 1994–2010.

[1]The ministry of labor estimates that above 90% of formally employed workers in Brazil were covered by RAIS throughout the 1990s. One benefit of this data is that the reports are substantially accurate. This accuracy stems from the fact that workers' public wage supplements rely on the RAIS information, which encourages workers to check if information is reported correctly by their employers.

[2]Using firms' identification codes to merge the RAIS data with customs data is a common practice in the literature studying the Brazilian trade activities (e.g., Aguayo-Tellez et al., 2010; Helpman et al., 2017; Dix-Carneiro et al., 2021).

Table B.1: Sample Statistics

Observations (72 million)	Non-exporter		Exporter	
	Mean	S.D.	Mean	S.D.
Panel A: workers' characteristics:				
age	31.96	9.72	32.80	9.39
schooling	8.06	3.46	8.94	3.78
log(hourly wage), Brazilian Real$	0.36	0.67	0.86	0.83
cognitive occupations (1 if yes)	0.19	0.39	0.24	0.43
production worker (1 if yes)	0.74	0.44	0.70	0.46
share of workers in the sample	0.47	–	0.53	–
Panel B: firms' characteristics:				
log(employment)	3.18	0.79	4.52	1.37
log(exports per worker), U.S.$	–	–	7.32	2.16
number of export destinations	–	–	5.56	8.45
ratio of # high-income to # total export destinations	–	–	0.34	0.38

Notes: We adjust log(hourly wage) for inflation using 1994 as the baseline year. Cognitive occupations refer to professionals, technicians, and other white-collar workers. Firm employment size is computed based on all workers within the firm in the raw sample (including female and part-time workers) to reflect actual firm size. *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms. The export value data is only available in 1997–2000, and hence log(exports per worker) is based on these four years.

We also have detailed data on export value and quantity by 8-digit HS products and destinations for the years 1997–2000.

B.1 Summary Statistics

Panel A of Table B.1 describes characterizations of the RAIS database, based on worker-firm-year observations. In our sample, 53% of worker-firm-year observations are at exporters, and thus export activity is nontrivial in our sample. On average, relative to workers at non-exporters, workers at exporters are slightly older and more educated, and earn higher hourly wages. Workers at exporters also tend to work in cognitive occupations (professionals, technicians, and other white-collar jobs) or as nonproduction workers.[3] Moreover, according to firms' characteristics in Panel B of Table B.1, exporters are much larger in terms of employment than non-exporters. These pieces of evidence on workers and firms are consistent with the exporter premium typically found in the literature (e.g., Bernard et al., 2003; Verhoogen, 2008). Finally, in our empirical analysis, we will study how returns to experience depend on firms' export destinations. On average, an exporter exports to 5.6 destinations, and among them 34% of destinations are high-income countries, where countries are classified as high-income countries according to the World Bank classification in

[3]In the Brazilian occupation classification (CBO-94), we consider occupations belonging to main groups 7, 8, and 9 (workers in industrial production, machine and vehicle operators, and similar workers) as production workers. The occupations in RAIS can be divided into 5 broad categories: professionals, technicians, other white-collar occupations, skilled blue collar occupations, and unskilled blue collar occupations. We consider skilled and unskilled blue collar jobs as manual occupations, and we treat professionals, technicians, and other white-collar occupations as cognitive occupations. The details about the Brazilian occupation classification can be found in Muendler et al. (2004).

2000.[4]

B.2 A First Glance at Experience-Wage Profiles

Using the raw data, we first show differences in experience-wage profiles between exporters and non-exporters in the cross section. We measure workers' potential experience as years elapsed since finishing schooling ($\min\{$age-18,age-6-schooling$\}$). In each year, we obtain experience-wage profiles by computing the average log hourly wage for workers in each 5-year experience bin $x \in \mathbb{X} = \{$1–5,6–10,...,36–40$\}$, separately for workers observed in exporting and non-exporting firms. Because we are interested in life-cycle wage growth, we normalize the value of the first experience bin (1–5 years of experience) to 0 for each experience-wage profile. Finally, we average profiles across years to obtain experience-wage profiles for exporters and non-exporters, respectively.

In Table B.2, we report the average log wage for workers with 36–40 years of experience relative to 1–5 years of experience (normalization). Column (1) in Panel A shows that, at exporters (non-exporters), the average log wage of workers with 36–40 years of experience is 0.73 (0.50) higher than workers with 1–5 years of experience.[5] This pattern holds in different time periods (Columns (2)–(3)) and after controlling for industry composition in Column (4). More notably, it is not caused by lower starting wages of workers at exporters. In the last two columns of Panel A, we recompute the average log wage of each experience bin relative to workers with 1–5 years of experience at non-exporters for any given year. We find that workers with 1–5 years of experience already have higher wages at exporters than at non-exporters. This gap grows larger as workers' experience increases.

In light of potential composition effects (exporters are larger and have a better workforce), in Panels B to D of Table B.2, we recompute the result in Column (1) of Panel A within the same workers' education levels, occupations, or firm size categories. Consistent with recent papers (Islam et al., 2019; Lagakos et al., 2018), we find that the experience-wage profile is steeper for workers with higher education levels (Panel B), in cognitive occupations (Panel C),[6] and in larger firms (Panel D). Moreover, we find that within all of these categories, workers have higher life-cycle wage growth at exporters than at non-exporters.

There are many identification problems with this first-pass attempt: for example, workers observed at exporters in a given year may have previously accumulated work experience at non-exporters in their earlier career. Nonetheless, the preliminary evidence from the raw data indicates that workers at exporters may have steeper experience-wage profiles than workers at non-exporters. We formally estimate experience-wage profiles in Section II.B.

[4] In 2000, the World Bank classifies countries into high-income countries if their GNI per capita is higher than $9,265. To avoid our results being affected by the reshuffling of countries around the margin, we still use our list of high-income countries in 2000 when we compute the results for other years. Our empirical results are robust if we consider changes in Brazil's relative income levels in the world, as shown in Section D.2.

[5] Our results are comparable to Lagakos et al. (2018) who use the Brazilian Population Census and document that the percent wage increase of 36–40 years of experience relative to 1–5 years of experience is around 60% (see Figure 1 in Lagakos et al. (2018)).

[6] Cognitive occupations refer to professionals, technicians, and other white-collar workers.

Table B.2: Average Log Wage of Workers with 36–40 Years of Experience Relative to 1–5 Years of Experience

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Aggregate profiles					
				controlling	rel. to non-exporters' first bin	
	all	1994–2000	2001–2010	for industry	first bin	40 years of exp
Exporter	0.73	0.67	0.77	0.65	0.30	1.03
Non-Exp	0.50	0.48	0.51	0.49	0	0.50
Difference	0.23	0.19	0.27	0.16	0.30	0.53
	Panel B: Aggregate profiles by education level					
	illiterate	primary	middle school	high school	college	
Exporter	0.23	0.70	0.85	1.29	1.42	
Non-Exp	0.18	0.46	0.56	0.83	1.08	
Difference	0.05	0.24	0.29	0.46	0.34	
	Panel C: Aggregate profiles by occupation					
	professionals	technical	other white-collar	Skilled blue-collar	unskilled blue-collar	
Exporter	1.11	0.97	0.51	0.57	0.23	
Non-Exp	0.86	0.70	0.34	0.44	0.16	
Difference	0.25	0.27	0.17	0.13	0.07	
	Panel D: Aggregate profiles by firm size					
	10-50	50-100	100-500	500-1000	1000+	
Exporter	0.54	0.61	0.69	0.76	0.79	
Non-Exp	0.43	0.50	0.58	0.57	0.45	
Difference	0.11	0.11	0.11	0.19	0.34	

Notes: This table reports the average log wage for workers with 36–40 years of experience relative to 1–5 years of experience (normalization). In each year, we obtain experience-wage profiles by computing the average log hourly wage for workers in each 5–year experience bin, separately for workers observed at exporters and non-exporters. We normalize the value of the first experience bin (1–5 years of experience) to 0 for each experience-wage profile. Finally, we average profiles across years to obtain experience-wage profiles for exporters and non-exporters, respectively. Columns (5)–(6) of Panel A use the average log wage of workers with 1–5 years of experience at non-exporters as normalization. In Column (4) of Panel A, we control for industry composition by first computing experience-wage profiles for workers at exporters and non-exporters in each industry, respectively. Then, we use the aggregate employment in each industry (aggregated over exporters and non-exporters) as weights to compute experience-wage profiles for workers at exporters and non-exporters, respectively. *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

C Empirical Method

C.1 HLT Method

To implement the HLT method, we define time trends $\{\zeta_{s,t}\}$ from time effects $\{\gamma_{s,t}\}$: $\zeta_{s,t} = \gamma_{s,t} - \gamma_{s,t-1}$. Thus, wage growth can be rewritten as:

$$\Delta \log(w_{i,t}) = \sum_{x \in \mathbb{X}} \phi_s^x D_{i,t}^x + \zeta_{s,t} + \epsilon_{i,t}. \tag{C.1}$$

The collinearity problem is that for each time t, $\zeta_{s,t} = 1$ is perfectly correlated with $\sum_x D_{i,t}^x = 1$, as explained in the main text. Using the assumption $\phi_s^{31-35} + \phi_s^{36-40} = 0$, we can solve the collinearity problem.

The HLT method in Lagakos et al. (2018) is slightly different. In Lagakos et al. (2018), we need to first decompose time effects into trend and cyclical components:

$$\gamma_{s,t} = g_s t + e_{s,t}, \tag{C.2}$$

where g_s denotes linear time trends. Thus, wage growth can be written as:

$$\Delta \log(w_{i,t}) = \sum_{x \in \mathbb{X}} \phi_s^x D_{i,t}^x + g_s + (e_{s,t} - e_{s,t-1}) + \epsilon_{i,t}. \tag{C.3}$$

We then restrict cyclical components to average zero over the time period $\sum_t e_{s,t} = 0$ and to be orthogonal to a time trend $\sum_t e_{s,t} t = 0$. These two restrictions reduce the freedom of $\{e_{s,t}\}$ by two and resolve the collinearity problem of time and experience returns ($e_{s,t}$ and $\sum_x D_{i,t}^x$), as also used in Deaton (1997) and Aguiar and Hurst (2013) in estimating life cycle profiles. To pin down the wage trend g_s, we exploit the additional assumption that there are no experience returns in the last 10 years of experience, $\phi_s^{31-35} + \phi_s^{36-40} = 0$.

In short, the first method transforms time effects $\{\gamma_{s,t}\}$ into trends $\{\zeta_{s,t}\}$, which naturally reduces the freedom of parameters by one, and then introduces one additional restriction $\phi_s^{31-35} + \phi_s^{36-40} = 0$ to solve the collinearity problem. The HLT method in Lagakos et al. (2018) adds two restrictions on original time effects γ_{st} and introduces one additional parameter g_s that requires one additional restriction $\phi_s^{31-35} + \phi_s^{36-40} = 0$ to pin down. Empirically, we find that these two different ways of dealing with time effects lead to very similar results.

C.2 Propensity Score Matching

We discuss the details of the propensity-score matching in Heckman, Ichimura and Todd (1997). We are interested in the average effects of exporting on the export entrants as follows:

$$E(y_\omega^1 - y_\omega^0 | D_\omega = 1) = E(y_\omega^1 | D_\omega = 1) - E(y_\omega^0 | D_\omega = 1). \tag{C.4}$$

where the superscript denotes the export status, and D is the dummy variable for starting to export. However, the challenge is that the counterfactual scenario of non-exporting $E(y_\omega^0 | D_\omega = 1)$ is not observable. In order to identify this group, we assume that all the differences between exporters and the appropriate control group can be captured by a set of observables X_ω. Specially, we first estimate each firm's probability $Pr(X_\omega)$ to start to export as a function of observables X_ω based on a Probit model. Then, based on the assumption that $y^0 \perp D | Pr(X)$, we can construct an estimate for the effect of exporting as follows,

$$\beta = \frac{1}{N_x} \sum_{\omega \in C_p \cap I_1} \left(y_\omega^1 - \sum_{\nu \in C_p \cap I_0} W(\omega, \nu) y_\nu^0 \right) \tag{C.5}$$

where C_p is the region of common support, and I_1 is the set of new exporters. N_x is the number of new exporters that are in the common support. I_0 is the set of non-exporters. $W(\omega, \nu)$ is the weight of each non-exporter ν in constructing the control group, with $\sum_{\nu \in C_p \cap I_0} W(\omega, \nu) = 1$

for each treated firm ω. In our main results, the matching is based on the method of the nearest neighbor, which selects a non-exporting firm that has a propensity score closest to that of the export entrant.

We can construct a DID estimator relative to the $\tau = -1$ period as follows,

$$DID = \frac{1}{N_x} \sum_{\omega \in C_p \cap I_1} \left(y^1_\omega - y^0_{\omega,-1} - \sum_{\nu \in C_p \cap I_0} W(\omega, \nu)(y^0_\nu - y^0_{\nu,-1}) \right) \tag{C.6}$$

where $y^0_{\omega,-1}$ is the outcome in the $\tau = -1$ period (previous period). We can also construct estimates of changes in future outcomes after starting to export following De Loecker (2007).

D Additional Empirical Results

D.1 Industry Composition and Returns to Experience

This difference in experience-wage profiles between exporters and non-exporters can be explained by different reasons. One important driver of the result can be industry composition. This is motivated by two well-established results in the literature: (1) different industries have different returns to experience (e.g., Dix-Carneiro, 2014; Islam et al., 2019); and (2) trade induces industry specialization and labor reallocation, possibly driven by comparative advantage (e.g., Costinot et al., 2012) or home market effects (e.g., Head and Ries, 2001). Therefore, if exporters are more concentrated in industries with higher returns to experience than non-exporters, exporters will on average also have steeper experience-wage profiles.

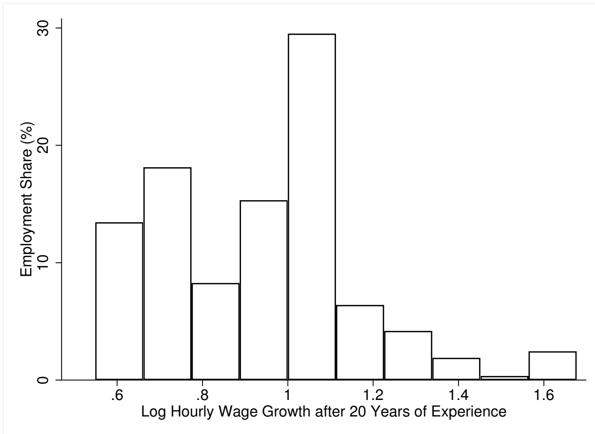
We first examine the role of industry composition in driving the difference of experience-wage profiles between exporters and non-exporters. We perform regression equation (1) separately for workers in each 3-digit manufacturing industry between 1994–2010. Figure D.1a illustrates the cross-industry distribution of wage growth for a hypothetical worker with 20 years of experience in the same industry, which is computed as $5 \times (\hat{\phi}^{1-5}_s + ... + \hat{\phi}^{16-20}_s)$. It is clear that there is a large degree of heterogeneity in returns to experience across industries.

Figure D.1b presents industry-level employment distributions in 1994–2010, for exporters and non-exporters respectively. We rank industries by returns to 20 years of experience, and for ease of description, we further split industries into 4 quartiles based on returns to experience. We find that more than 59% of workers at exporters are employed in industries with lower returns to experience than the median, similar to around 62% for non-exporters.

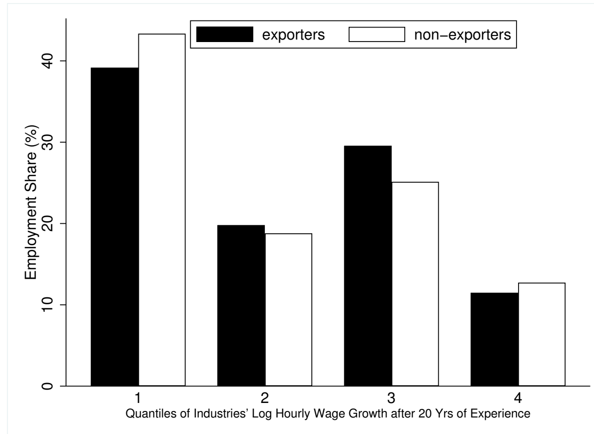
These findings have two main implications. First, trade changes workers' allocation across industries with heterogeneous returns to experience, as similarly found by Dix-Carneiro (2014). This force can generate gains or losses in workers' earnings growth, depending on each country's specialization pattern. For countries with comparative advantage in industries with higher returns to experience, trade openness can lead to higher earnings growth. On the other hand, for other countries, trade openness can generate lower earnings growth by allocating workers toward industries with lower returns to experience.

Second, in Brazil, industry composition is not important for the aggregate difference in returns to experience between exporters and non-exporters. Using industry-specific returns to experience

Figure D.1: Returns to Experience and Industry Heterogeneity



(a) Distribution of Log Hourly Wage Increase Across Industries



(b) Distribution of Employment by Exporters and Non-exporters

Notes: This graph presents the results from estimating equation (1), separately for workers in each 3-digit manufacturing industry between 1994–2010. Panel (a) is the cross-industry distribution of returns to 20 years of experience. Panel (b) presents the employment distribution of workers at exporters and non-exporters across industries ordered by different quartiles of returns to 20 years of experience. *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

and different employment distributions across industries for exporters and non-exporters, we find that after 20 years of experience, workers' wage increase would be 1 percentage point higher at exporters than at non-exporters due to industry composition.

D.2 Robustness Checks of Table 1

Classification of high-income destinations. Considering that Brazil's fast economic growth in the 1990s and 2000s may change its relative position with regard to export destinations, we now use each year's country-level GDP per capita. In Table D.2, we construct exposure to high-income destinations using the ratio of the number of export destinations with higher-than-Brazil GDP per capita in the corresponding year to the total number of destinations, or export-weighted GDP per capita across destinations (relative to Brazil's GDP per capita) in the corresponding year.[7] We find quantitatively similar impacts of export activity on experience returns compared with our baseline results in Table 1.

Discussion of the HLT assumption. We assumed the final 10 years of no experience effects to construct firm-specific wage trends. Table D.3 shows that the coefficients are similar to those in Table 1 if we assume the final 5 years with no experience returns.

Another issue is that young and senior workers may be different in many aspects (e.g., education levels), and thus senior workers' wage growth may not represent young workers' wage growth

[7] In unreported results, we also experimented with many other thresholds on yearly GDP per capita to define high-income destinations (for example, a destination is defined to be high-income if its GDP per capita exceeds Brazil's by 100% in the corresponding year), and found similar empirical results as in Table 1. These results are available upon request.

in the absence of returns to experience. To rule out this issue, we directly regress the average yearly wage growth of workers in each experience bin on the exporter dummy and exposure to high-income destinations, controlling for the corresponding workers' characteristics (education, occupation, and age) and thus allowing for different characteristics of young and senior workers to affect their respective wage growth. This approach echoes recent papers which infer the strength of human capital accumulation directly through wage growth differentials across individuals (e.g., Herkenhoff et al., 2018; Jarosch, Oberfield and Rossi-Hansberg, 2021).

In Table D.4, we report the regression results and show that young workers' wage growth is significantly faster with more exposure to high-income export destinations, whereas senior workers' wage growth is insensitive to high-income destinations. Thus, our previously found impact of export destinations on experience returns is indeed driven by wage growth differentials between young and senior workers regarding exposure to high-income destinations rather than workers' different observed characteristics.

Workers' and firms' past experience at exporters. Recent research suggests that past experience of managers and coworkers at exporters facilitates exporting (Mion and Opromolla, 2014; Muendler and Rauch, 2018). In Table D.5, we replicate the results in Table 1, after controlling for duration of workers' previous experience at exporters and duration of the firm's previous export participation, as well as these durations related to high-income destinations. The coefficients of interest barely change, suggesting that our findings are not driven by working with experienced managers and coworkers.

Role of tenure. Our estimates on experience returns may be confounded by tenure effects, as low tenure at the current firm may also lead to fast wage growth (Topel, 1991; Dustmann and Meghir, 2005). In Table D.6, we control for workers' average tenure and the difference in average tenure between young and senior workers within the firm, and we find that the coefficients of interest barely change compared with our baseline results in Table 1.

Role of product quality. One possible explanation of destination-specific experience returns is that exporting to high-income destinations may require high-quality goods, which may lead to changes in workers' skills. Whereas it is difficult to directly observe export quality, one observation is that product quality is positively correlated with export prices (Schott, 2004; Manova and Zhang, 2012). In Table D.7, we construct firm-year-level export prices in the period of 1997–2000[8] and show that controlling for average export prices does not affect our estimated impact of high-income destinations on wage profiles, indicating that quality upgrading may not be the driver for this destination-specific impact.

Female employees. In our baseline results, we focus on male employees to avoid selection issues regarding female labor participation. As shown in Table D.8, in line with our findings for

[8]Because unit prices are not directly comparable across products, we first compute firms' unit prices of products relative to average unit prices of exports to Argentina (which is of similar development levels to Brazil) for each 8-digit product and year. We then use export volume as weights to compute a weighted average unit price of exports for each firm and year. The results are quantitatively similar if we use the U.S. as the benchmark country to construct relative unit prices of products.

male employees, we find quantitatively similar impacts of high-income destinations on experience returns for female employees.

Industry heterogeneity in destination-specific returns. We now explore how the impact of export destinations on experience returns varies across industries. In Table D.8, we divide industries into differentiated and non-differentiated industries.[9] We show that workers in differentiated industries enjoy large and significant increases in returns to experience due to high-income destinations, whereas workers in non-differentiated industries have insignificant and small changes in returns due to destinations. This indicates that our finding may be partly driven by workers' human capital accumulation, as differentiated products tend to be associated with larger scope of workers' learning opportunities.[10]

Our main analysis focuses on manufacturing, whereas Brazil also exports agricultural and mining products (see Section A.1). Table D.8 reports that there are no significant experience effects of export destinations on agricultural and mining firms, whose products tend to be more homogeneous with little scope of learning.

Heterogeneity in destination-specific returns across firms. In Table D.9, we explore how the impact of export destinations varies with firm characteristics by incorporating the interaction between firm characteristics and exposure to high-income destinations into the regression of Column (3) in Table 1. We find that the impact of export destinations on experience returns does not vary significantly with the workforce's education levels, occupation structure, and average age, as well as the firm's employment size.[11]

D.3 Event Study

We proceed to perform an event study to show that changes in returns to experience related to high-income destinations materialize immediately when firms start exporting. To this end we run

[9] Using the firm-product-level export value in 1997–2000, we define a 3-digit industry to be differentiated if its share of differentiated-product exports in total exports lies above the median across all manufacturing industries, according to the classification of 4-digit SITC products in Rauch (1999).

[10] For example, as Artopoulos, Friel and Hallak (2013) note in Latin America, successfully entering markets in developed economies with differentiated products requires potential exporters to make substantial efforts to upgrade the physical characteristics of their products and their marketing practices.

[11] Mion and Ottaviano (2020) find higher wage profiles for managers (a subset of nonproduction workers) in internationally active firms in Portugal. In our sample, we do not find our estimated impact of export destinations on wage profiles changes significantly with the share of managers in the firm's workforce, as shown in Column (6) of Table D.9, where managers include senior managers and supervisors according to Muendler et al. (2004). In Table D.8, we construct firm-year-level experience returns separately for production and nonproduction workers. We do not find the impact of exposure to high-income destinations on experience returns is significantly different between production and nonproduction workers. However, due to the small portion of nonproduction workers within firms (around 30%), the impact of export destinations on nonproduction workers' wage profiles is noisily estimated and insignificant. As managers only make up a very small portion (4%) of a firm's workforce in our sample, we do not construct experience returns separately for managers.

the following regression:

$$\begin{aligned}y_{\omega,t} = &\sum_{\tau=-4}^{\tau=-2} \beta_\tau 1\{high\_inc\}_{\omega,t^*+\tau} + \sum_{\tau=0}^{\tau=4} \beta_\tau 1\{high\_inc\}_{\omega,t^*+\tau} + \beta_{pre} \sum_{\tau\leq-5} 1\{high\_inc\}_{\omega,t^*+\tau}\\ &+ \beta_{post} \sum_{\tau\geq5} 1\{high\_inc\}_{\omega,t^*+\tau} + \mathbf{X}'_{\omega,t}\mathbf{b} + \theta_\omega + \psi_{j(\omega,t)} + \delta_t + \epsilon_{\omega,t}.\end{aligned} \tag{D.1}$$

As before, the dependent variable $y_{\omega,t}$ is firm-year-level returns to 20 years of experience. We still control for firm fixed effects θ_ω, industry effects $\psi_{j(\omega,t)}$, and year effects δ_t. Firm-level controls $\mathbf{X}_{\omega,t}$ include all the control variables in Table 1, and a dummy variable indicating whether the firm is exporting to a non-high-income destination.

The β_τ parameters of primary interest are coefficients on indicators for time periods relative to the firm's first export entry into high-income destinations at time $t = t^*$ ($\tau = 0$). We exclude an indicator for the period immediately before the firm's export entry, and hence the parameters represent changes in returns to experience relative to the period before entry into high-income destinations. The coefficients are identified by firms starting as non-exporters or exporters only to non-high-income destinations and then turning to export to high-income destinations in our sample period. Thus, in the analysis, we focus on firms that do not start as exporters to high-income destinations when they make first appearance in the sample. For the β_τ parameters after entry, we also require that firms remain exporting to high-income destinations, and therefore β_τ (for $\tau > 0$) is interpreted as changes in returns to experience for a firm that exports to high-income destinations in τ periods after first entry.

Figure D.4 presents the results from estimating equation (D.1). After first entry into high-income destinations, firms' returns to experience significantly increase by 20 percentage points, whereas experience-wage profiles do not significantly shift before firms' export entry.[12] In addition, the increase in returns to experience stays roughly constant after entry, indicating that exporting to high-income destinations is associated with persistently higher returns to experience. Figure D.5 estimates the β_τ parameters for the firm's first export entry into non-high-income destinations at time $t = t^*$ ($\tau = 0$). We find no significantly positive changes in returns to experience after entry to non-high-income destinations.[13]

Figure D.4 also shows that most of the gains in returns to experience materialize immediately after entry to high-income destinations ($\beta_0 = 0.20$) and slightly increase in three years after export entry ($\beta_3 = 0.23$). This pattern is consistent with De Loecker (2007) who finds that the immediate firm productivity gain after export entry is large, and that the gain only slightly changes after export entry. Figure D.6 reports the impact of entry into high-income destinations on experience returns

[12]The average difference in returns to 20 years of experience between pre-exporting periods ($\tau = -5$ to $\tau = -1$) and after-exporting periods ($\tau = 0$ to $\tau = 5$) is 0.15 (p-value=0.006), suggesting significantly positive gains in returns to experience after export entry to high-income destinations.

[13]Figure D.7 estimates the β_τ parameters for the firm's first export entry regardless of destinations, and the estimated coefficients are between the effect of exporting to high-income destinations and that of exporting to non-high-income destinations. Although the impact of firms' first export entry regardless of destinations tends to be small, in the data, conditional on being an exporter, larger firms export more to richer destinations: the share of exporters that export to high-income destinations is 15 percentage points higher for firms with above-median employment levels than firms with below-median employment levels. This pattern suggests that the aggregate impact tends to reflect the effect of high-income destinations.

for workers in different life cycle stages. The increase in the impact after years of export entry mainly occurs for the youngest workers (with 1–5 years of experience), indicating that the youngest workers may enjoy slightly larger benefits over time after export entry, though the increase is relatively mild compared with the immediate response. This immediate response will be consistent with the mechanisms exploited (worker-firm rent sharing and human capital) in our model, as exporting to high-income destinations immediately changes the scope of worker-firm rent sharing and the human capital increment per time spent.

D.4 Propensity Score Matching Estimator

To control for self-selection into exporting, we apply the propensity-score matching estimator (Heckman, Ichimura and Todd, 1997, see Section C.2 for details).[14] The key of this matching estimator is choosing an appropriate set of non-exporters based on export probability as the control group for exporters. The assumption of identification is that conditional on export probability, firms' performance (in the absence of exporting) is independent of the current export status, and thus we can use the performance of the control group to proxy the counterfactual scenario of no export entry for exporters. This assumption is more likely to hold when we estimate the export probability based on a larger set of firms' observables.

Thus, we first estimate each firm's probability to start to export to high-income destinations based on a Probit model, controlling for a wide range of pre-exporting (previous year) firm characteristics, including returns to experience, workers' education levels, workers' occupation structure, workers' average age, firm size, and export status to non-high-income destinations, as well as industry and year fixed effects. We then choose the matched control group based on the method of the nearest neighbor,[15] which selects a non-exporting firm which has an export probability closest to that of the export entrant. Table D.10 reports the t-tests showing that all the observables (used in constructing the export probability) are similar between the chosen control group and the export entrants, and thus our matching estimator satisfies the balancing hypothesis (see Rosenbaum and Rubin (1984)).

Panel (a) of Table D.11 reports the difference in the level of returns to experience between new exporters and non-exporters, and Panel (b) presents the difference in growth of returns (relative to $\tau = -1$ period) between new exporters and non-exporters, which can be interpreted as a DID estimator. These estimators are constructed in the same way as in De Loecker (2007). We report the differences in the period of export entry ($\tau = 0$) and up to 3 periods after export entry for firms that remain exporting. Our results show that exporting to high-income destinations causes an increase in returns to experience. Most of the estimated increases in returns to 20 years of experience are significant and at around 20 percentage points, similar to our estimates in Table 1 and Figure D.4.

Table D.12 reports future effects for new exporters that stop exporting in future periods. Increases in returns to experience become much smaller after firms stop exporting, and the statistical significance vanishes. This suggests that large increases in returns to experience are associated with continuing exporting to high-income destinations. Finally, Table D.13 replicates Table D.11

[14] Previous studies have used the matching estimator to estimate the productivity effects of exporting (Wagner, 2002; Girma et al., 2003; De Loecker, 2007; Konings and Vandenbussche, 2008; Ma et al., 2014).

[15] We also experimented with kernel matching or one-to-one Mahalanobis matching. We still find quantitatively similar results: exporting to high-income countries increases returns to experience.

for entry to non-high-income destinations, and we find no statistically significant changes in returns to experience after export entry.

D.5 Case Study: Brazilian Currency Crisis 1999

To corroborate our argument that export activities change returns to experience, we describe an event study using the 1999 currency devaluation, which led to a quasi-experimental surge in Brazilian firms' export activities.

In January and February 1999, Brazil experienced a massive devaluation of its domestic currency, with the Brazilian Real per U.S. dollar increasing from 1.20 in December 1998 to 1.93 in February 1999, a 60% devaluation within two months.[16] The abrupt currency devaluation was detrimental to the economy in many ways, but nonetheless it improved Brazilian firms' competitiveness in the global market and induced more firms to export. In Figure D.8b, we show that the probability of firms exporting strongly increased after 1999 (relative to year 1998, after controlling for firm fixed effects and industry fixed effects), while there was no effect in the year prior to the large devaluation episode and a small increase in the previous years. Similarly, Verhoogen (2008) finds that the Mexican peso crisis in 1994 led to more firms' entry into exporting, and Macis and Schivardi (2016) finds the 1992 devaluation of the Italian lira also led to higher export shares of sales.

We exploit this large devaluation episode and apply a DID approach to analyze how exporting affects experience-wage profiles due to exogenous shifts (from individual firms' perspective) in exporting opportunities. Following Macis and Schivardi (2016), we perform the following regression:

$$\begin{aligned} y_{\omega,t} =& \beta_0 + \beta_1 Exporter_{\omega,t} \times DV + \beta_2 Exporter_{\omega,PRE} \times DV + \beta_3 Exporter_{\omega,t} \times (1 - DV) \\ &+ \gamma_1 Ratio\_high_{\omega,t} \times DV + \gamma_2 Ratio\_high_{\omega,PRE} \times DV + \gamma_3 Ratio\_high_{\omega,t} \times (1 - DV) \\ &+ \mathbf{X}'_{\omega,t}\mathbf{b} + \theta_\omega + \psi_{j(\omega,t)} + \delta_t + \epsilon_{\omega,t}. \end{aligned} \tag{D.2}$$

The dependent variable is still firm-year-level returns to 20 years of experience. DV is a dummy variable indicating the post-devaluation period (1999 or later). $Exporter_{\omega,t}$ is the dummy variable indicating the export status, and $Ratio\_high_{\omega,t}$ is the ratio of the number of high-income destinations to the total number of destinations, measuring exposure to high-income destinations. $Exporter_{\omega,PRE}$ and $Ratio\_high_{\omega,PRE}$ are the average of export status and exposure to high-income destinations during the pre-devaluation period (1996–1998), respectively. We control for a set of firm and workforce characteristics $\mathbf{X}_{\omega,t}$, firm fixed effects θ_ω, industry fixed effects $\psi_{j(\omega,t)}$, and year fixed effects δ_t. In the post-devaluation period ($DV = 1$), our empirical analysis controls for the impact of pre-existing export patterns on returns to experience by including the interaction between pre-exporting export patterns (export status and exposure to high-income destinations) and the devaluation dummy DV. By doing this, we allow for the possibility that determinants of the export pattern in the pre-devaluation period might have also affected returns to experience,

[16] The devaluation came as a surprise, and many factors may have led to this crisis. Many economists believed that the crisis had roots in the financial turmoil following the Asian financial crisis and fundamental problems of the Brazilian economy (such as budget and current account deficits). For a thorough discussion of the Brazilian currency crisis, see https://www.nber.org/crisis/brazil_report.html.

which could persist in the post-evaluation period; moreover, we can also control for the potential lagged effect of the past export performance on outcomes in the post-devaluation period.

In this DID design, we impose two implicit assumptions for identification: (1) most changes in firms' export status after 1999 were due to improved competitiveness with currency devaluation; and (2) this currency devaluation affected returns to experience through changes in export activities, but was uncorrelated with other factors that can shift returns to experience. These assumptions are more likely to be true within a narrow time frame of the currency crisis; therefore, we estimate equation (D.2) using the observations within 1–3 years around the episode year, 1999.

Table D.14 presents the results. Regardless of the chosen time frame, the results show that the interaction between exposure to high-income destinations and the devaluation dummy is always significantly positive. This indicates that entry into high-income destinations induced by the currency devaluation increased returns to experience.

D.6 Panel Estimation of Workers' Experience Effects

In this section, we track workers over time and estimate how workers' experience affects workers' current wages. We consider the following Mincer regression:

$$\log w_{i,k,t} = \theta_k Eduyrs_{i,t} + \sum_{x\in\mathbb{X}} \sum_{k'\in\{e,n\}} \phi^x_{k'} Exp^x_{i,k'} + \mu_i + \theta_{\omega(i,t)} + \delta_{k,t} + \epsilon_{i,k,t}, \tag{D.3}$$

where i, ω, k and t represent individual, firm, firm export status, and time, respectively. $w_{i,k,t}$ is the hourly wage for an individual i currently working in firms of export status $k \in \{e, n\}$, either exporters (e) or non-exporters (n). The variable $Eduyrs_{i,t}$ represents schooling, of which the returns can depend on the current firm type. The variable $Exp^x_{i,k'}$ denotes her accumulated years of experience in type-k' firms ($k' \in \{e, n\}$) in each experience bin x of her work history (before current year). $\phi^x_{k'}$ refers to the effect of a one-year increase in experience $Exp^x_{i,k'}$ on current wages. We let $\phi^x_{k'}$ differ across experience bins to capture that experience returns vary across different stages of life: for example, one year of experience accumulated just after entry of the labor market could have different effects compared with one year of experience accumulated in a later life stage. μ_i is a vector of individual fixed effects; $\theta_{\omega(i,t)}$ is the fixed effect of the firm hiring worker i in time t; and $\delta_{k,t}$ is a vector of time effects specific to firm export status. We also control for industry effects and firm-year-level workforce characteristics as in Table 1 (for the firm currently hiring the worker), which are not specified in the equation to save notation.

To proceed with estimation of our regression in equation (D.3), we construct a panel of workers such that their work history can be fully observed. To achieve this goal, we supplement our sample in 1994–2010 with the RAIS data in 1986–1993, for which we do not observe hourly wage but can use these years' data to construct workers' experience. We focus on workers that first appeared in the database within 5 years after finishing schooling[17] and construct their full employment history

[17] This aims to rule out old workers for whom we do not observe their previous employment history, particularly those who started work before 1986 or were employed in the informal sector in their early life. The age of finishing schooling is constructed as $\max\{\text{schooling} + 6, 18\}$, where we consider the starting age of schools to be 6 and also require the earliest age of entering the labor market to be 18, according to the literature (Lagakos et al., 2018). We experimented with different thresholds on workers (e.g., within 2 years after finishing schooling), and the results are quantitatively very similar.

in RAIS. As workers may disappear in some years' RAIS data, the actual work history constructed from the RAIS data does not have the collinearity problem with the year effects. Our results are robust if we use the sample of workers that do not have breaks in their work history in the RAIS data. By construction, due to the time length of our sample, the highest observed experience is 25 years. As we do not restrict workers' wages to be within a job, we can explore how experience affects wages after workers switch firms.

Column (1) of Table D.15 reports the estimation results. We do not report the returns to 21–25 years of experience, for which there are few observations and thus the estimates are noisy. The results show that returns to schooling are small, because after controlling individual fixed effects, identification of returns to education depends on within-individual changes in schooling over time (subject to large noises). Instead, a cross-sectional Mincer regression indicates that the return to education is 8.6% per year of schooling, in close accord with the literature (e.g., Young, 2013). More importantly, according to our estimation results, if a new worker with average schooling (9 years) starts her job at exporters, she enjoys a $-0.018 + 0.003 \times 9 = 0.9\%$ wage premium relative to a job at non-exporters. If she continues to work at exporters, her wage growth is 15 percentage points higher than working at non-exporters over 20 years of experience, in line with our estimation results in Section II.B.

Column (2) introduces the years of working at exporters/non-exporters in the same firm as the current firm into regression (D.3), as experience in the same firm may capture firm-specific factors (e.g., firm-specific learning or changes in bargaining positions) and lead to higher wages. Due to the space constraints, we do not present the coefficients on the years of working at non-exporters in the same firm as the current firm. We indeed find that the previous experience in the same firm is more valuable. However, after controlling for same-firm effects, we still find sizable returns to previous experience at exporters. According to the estimates, if a worker starts to work in a new firm after 20 years of experience at exporters, she would enjoy a 11% higher wage than previously working at non-exporters for 20 years.

In Column (3) of Table D.15, we introduce the interaction between the years of working at exporters and the ratio of the amount of high-income destinations to the amount of all destinations into regression (D.3), in order to explore the destination-specific effects. According to the results, we find that if a worker accumulates 20 years of experience at exporters from the beginning of the career, working at exporters that only export to high-income destinations would lead to a 7% higher wage than working at exporters that only export to non-high-income destinations. This result is in similar magnitude to our firm-level results in Table 1.

Finally, we analyze a sample of involuntarily displaced workers because their returns to previous experience are more likely to be shaped by learning than seniority after displacement, following the labor literature (Jacobson, LaLonde and Sullivan, 1993; Dustmann and Meghir, 2005; Arellano-Bover and Saltiel, 2021). We focus on the events of firm closure, which we define as that large firms (with more than 50 employees) close down and do not subsequently show up. We identify 5,633 events of manufacturing firm closure between 1994–2010. We consider employees who were employed in the year of firm closure and study how their experience affected their post-displacement earnings (at first appearance after displacement). In Columns (4)–(6), we replicate Columns (1)–(3) using displaced workers' earnings, except that we do not control for workers' fixed effects as few workers have experienced multiple displacement events. We still find that previous experience at exporters is more valuable than previous experience at non-exporters, especially when exporters sell to high-income destinations. In particular, if a worker has accumulated 20 years of experience at exporters before displacement, previously working at exporters that only export to high-income destinations would lead to a 12% higher post-displacement wage than previously working at exporters that only export to non-high-income destinations.

D.7 Tables and Graphs

Table D.1: Wage Profiles and Control Variables

	Dep Var: Firm-year-level Returns to 20 Yrs of Experience						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Sample period	94–10	94–10	94–10	94–10	94–10	94–10	94–10
Exporter	0.278***	0.237***	0.275***	0.272***	0.258***	0.132***	0.021
	(0.013)	(0.014)	(0.013)	(0.013)	(0.013)	(0.016)	(0.030)
Average years of schooling		0.013**					-0.012
		(0.006)					(0.012)
Share of high-school graduates		0.324***					0.037
		(0.048)					(0.097)
Average workers' age			0.008***				-0.047***
			(0.002)				(0.005)
Share of production workers				-0.212***			0.006
				(0.036)			(0.100)
Share of occupations intensive in cognitive tasks					0.385***		0.241**
					(0.041)		(0.119)
Log firm employment						0.067***	0.025
						(0.011)	(0.030)
Firm employment percentile (0–10%)						-0.296***	-0.261**
						(0.062)	(0.119)
Firm employment percentile (10–20%)						-0.189***	-0.077
						(0.062)	(0.110)
Firm employment percentile (20–30%)						-0.247***	-0.120
						(0.052)	(0.095)
Firm employment percentile (30–40%)						-0.147***	-0.001
						(0.045)	(0.083)
Firm employment percentile (40–50%)						-0.158***	-0.094
						(0.040)	(0.074)
Firm employment percentile (50–60%)						-0.135***	-0.010
						(0.035)	(0.065)
Firm employment percentile (60–70%)						-0.124***	-0.026
						(0.031)	(0.056)
Firm employment percentile (70–80%)						-0.085***	0.017
						(0.026)	(0.046)
Firm employment percentile (80–90%)						-0.061***	0.014
						(0.021)	(0.033)
Industry and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No	No	No	Yes
Obs	344,658	344,658	344,658	344,658	344,658	344,658	344,658
R-squared	0.007	0.007	0.007	0.007	0.007	0.008	0.319

Notes: This table presents estimates from regressions of firm-year-level returns to 20 years of experience on firm characteristics. The reference group is non-exporters in the upper 10% of firm employment distribution within each industry-year. Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%. *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

Table D.2: Wage Profiles and Firm Characteristics (Using Each Year's Income)

	Firm-year-level Returns to 20 Yrs of Experience			
	(1)	(2)	(3)	(4)
Sample period	94–10	97–00	97–00	97–00
Exporter	-0.052	-0.105	-0.115	-0.042
	(0.045)	(0.097)	(0.137)	(0.125)
Exporter × ratio of	0.110**	0.167*		
# richer-than-Brazil dests to # total dests	(0.048)	(0.102)		
Exporter × share of			0.143	
exports to richer-than-Brazil dests			(0.098)	
Exporter ×				0.101*
log(avg GDPPC of dests relative to Brazil)				(0.055)
Exporter ×	-0.004	0.047	0.034	0.030
log(# total dests)	(0.020)	(0.053)	(0.060)	(0.060)
Exporter ×			0.006	0.006
log(avg exports per employee)			(0.022)	(0.022)
Industry and Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Obs	344,658	77,847	77,847	77,847
R-squared	0.319	0.489	0.489	0.489

Notes: This table presents estimates from regressions of firm-year-level returns to 20 years of experience on firm characteristics. The reference group is non-exporters. Controls: average years of schooling; share of workers with high-school degree; share of occupations intensive in cognitive tasks; share of production workers; average worker age; firm employment; and firm employment percentiles (divided into 10 bins) within each industry-year bin. Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%. *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

Table D.3: Wage Profiles and Firm Characteristics (With No Experience Returns in Final 5 Years)

	Dep Var: Firm-year-level Returns to 20 Yrs of Experience					
	(1)	(2)	(3)	(4)	(5)	(6)
Sample period	94–10	94–10	94–10	97–00	97–00	97–00
Exporter	0.238***	0.027	0.005	-0.073	-0.150	-0.121
	(0.018)	(0.041)	(0.049)	(0.094)	(0.167)	(0.165)
Exporter × ratio of			0.140**	0.195		
# high-income to # total dests			(0.068)	(0.141)		
Exporter × share of					0.174	
exports to high-income dests					(0.131)	
Exporter ×						0.165**
log(avg GDPPC of dests)						(0.076)
Exporter ×			-0.038	-0.040	-0.063	-0.064
log(# total dests)			(0.026)	(0.070)	(0.079)	(0.079)
Exporter ×					0.017	0.015
log(avg exports per employee)					(0.029)	(0.029)
Industry and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes	Yes
Obs	242,669	242,669	242,669	54,712	54,712	54,712
R-squared	0.005	0.326	0.326	0.505	0.505	0.505

Notes: This table presents estimates from regressions of firm-year-level returns to 20 years of experience on firm characteristics. The reference group is non-exporters. Controls: average years of schooling; share of workers with high-school degree; share of occupations intensive in cognitive tasks; share of production workers; average worker age; firm employment; and firm employment percentiles (divided into 10 bins) within each industry-year bin. Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%. *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

Table D.4: Average Wage Growth and Firm Characteristics

	Dep Var: Average Yearly Wage Growth							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample period	94–10	94–10	94–10	94–10	94–10	94–10	94–10	94–10
Experience bin	1–5	6–10	11–15	16–20	21–25	26–30	31–35	36–40
Exporter	-0.002	-0.005***	-0.004***	-0.005***	-0.003*	-0.003*	-0.004**	-0.004*
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Exporter $\times$ ratio of	0.006**	0.007***	0.002	0.004*	0.000	0.002	0.000	-0.001
#high-income to #total dests	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
Industry and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	344,658	344,658	344,658	344,658	312,083	295,140	305,180	242,661
R-squared	0.386	0.418	0.411	0.405	0.409	0.391	0.376	0.368

Notes: The reference group is non-exporters. The controls (specific to each experience bin in each firm and year) are: 1) average years of schooling; 2) share of workers with high-school degree; 3) share of occupations intensive in cognitive tasks; 4) share of production workers; 5) average worker age; 6) firm employment; and 7) firm employment percentiles (divided into 10 bins) within each industry-year bin. Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%. *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

Table D.5: Wage Profiles and Firm Characteristics (Controlling for Previous Experience)

	Dep Var: Firm-year-level Returns to 20 Yrs of Experience					
	(1)	(2)	(3)	(4)	(5)	(6)
Sample period	94–10	94–10	94–10	97–00	97–00	97–00
Exporter	0.278***	0.025	-0.012	-0.051	-0.116	-0.084
	(0.013)	(0.031)	(0.034)	(0.073)	(0.126)	(0.125)
Exporter × ratio of # high-income to # total dests			0.127**	0.237**		
			(0.053)	(0.112)		
Exporter × share of exports to high-income dests					0.183*	
					(0.105)	
Exporter × log(avg GDPPC of dests)						0.131**
						(0.063)
Exporter × log(# total dests)			-0.028	0.004	-0.016	-0.015
			(0.043)	(0.104)	(0.107)	(0.107)
Exporter × log(avg exports per employee)					0.015	0.013
					(0.020)	(0.020)
Duration of workers' previous experience at exporters		-0.055**	-0.050**	-0.138	-0.139	-0.139
		(0.024)	(0.024)	(0.108)	(0.108)	(0.108)
Duration of workers' previous experience at exporters (high-income dests)		0.060**	0.051*	-0.081	-0.085	-0.085
		(0.028)	(0.028)	(0.123)	(0.123)	(0.123)
Duration of firms' previous export participation		0.001	-0.002	0.048	0.053	0.049
		(0.012)	(0.012)	(0.072)	(0.071)	(0.072)
Duration of firms' previous export participation (high-income dests)		-0.015	-0.010	0.024	0.019	0.021
		(0.014)	(0.014)	(0.079)	(0.079)	(0.079)
Industry and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes	Yes
Obs	344,658	344,658	344,658	77,847	77,847	77,847
R-squared	0.007	0.319	0.319	0.490	0.490	0.490

Notes: This table presents estimates from regressions of firm-year-level returns to 20 years of experience on firm characteristics. The reference group is non-exporters. Controls: average years of schooling; share of workers with high-school degree; share of occupations intensive in cognitive tasks; share of production workers; average worker age; firm employment; and firm employment percentiles (divided into 10 bins) within each industry-year bin. Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%. We define the duration as follows. Duration of workers' previous experience at exporters: we compute each worker's duration of work history (before current year) at exporters and then take the average across all workers at the current firm in the current year. Duration of workers' previous experience at exporters (high-income dests): we compute each worker's duration of work history (before current year) at exporters that export to high-income destinations and then take the average across all workers at the current firm in the current year. Duration of firms' previous export participation: we compute the firm's duration of export participation (before current year). Duration of firms' previous export participation (high-income dests): we compute the firm's duration of export participation in high-income destinations (before current year). *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

Table D.6: Wage Profiles and Firm Characteristics (Controlling for Tenure)

	Dep Var: Firm-year-level Returns to 20 Yrs of Experience					
	(1)	(2)	(3)	(4)	(5)	(6)
Sample period	94–10	94–10	94–10	97–00	97–00	97–00
Exporter	0.278***	0.023	-0.012	-0.051	-0.069	-0.036
	(0.013)	(0.030)	(0.035)	(0.073)	(0.127)	(0.126)
Exporter × ratio of # high-income to # total dests			0.133***	0.241**		
			(0.052)	(0.110)		
Exporter × share of exports to high-income dests					0.184*	
					(0.104)	
Exporter × log(avg GDPPC of dests)						0.129**
						(0.062)
Exporter × log(# total dests)			-0.007	0.039	0.030	0.030
			(0.020)	(0.053)	(0.060)	(0.060)
Exporter × log(avg exports per employee)					0.007	0.005
					(0.022)	(0.022)
Average workers' tenure (in years)		-0.049***	-0.049***	-0.077***	-0.077***	-0.077***
		(0.009)	(0.009)	(0.027)	(0.027)	(0.027)
Difference in average tenure between young and senior workers (in years)		-0.029***	-0.029***	-0.038***	-0.038***	-0.038***
		(0.004)	(0.004)	(0.010)	(0.010)	(0.010)
Industry and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes	Yes
Obs	344,658	344,658	344,658	77,847	77,847	77,847
R-squared	0.007	0.319	0.319	0.490	0.490	0.490

Notes: This table presents estimates from regressions of firm-year-level returns to 20 years of experience on firm characteristics. Senior workers refer to workers in experience bins of 31–40 years, whereas young workers refer to workers in experience bins of 1–20 years. The reference group is non-exporters. Controls: average years of schooling; share of workers with high-school degree; share of occupations intensive in cognitive tasks; share of production workers; average worker age; firm employment; and firm employment percentiles (divided into 10 bins) within each industry-year bin. Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%. *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

Table D.7: Wage Profiles and Firm Characteristics (Controlling for Product Prices)

	Dep Var: Firm-year-level Returns to 20 Yrs of Experience					
	(1)	(2)	(3)	(4)	(5)	(6)
Sample period	97–00	97–00	97–00	97–00	97–00	97–00
Exporter	-0.095	-0.096	-0.071	-0.072	-0.037	-0.039
	(0.128)	(0.128)	(0.127)	(0.127)	(0.126)	(0.126)
Exporter × ratio of	0.239**	0.240**				
# high-income to # total dests	(0.110)	(0.110)				
Exporter × share of			0.183*	0.183*		
exports to high-income dests			(0.104)	(0.104)		
Exporter ×					0.128**	0.129**
log(avg GDPPC of dests)					(0.062)	(0.062)
Exporter ×	0.028	0.027	0.029	0.029	0.029	0.029
log(# total dests)	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)
Exporter ×	0.009	0.009	0.007	0.008	0.006	0.006
log(avg exports per employee)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Exporter ×		-0.006		-0.006		-0.006
log(avg unit prices of exports)		(0.014)		(0.014)		(0.014)
Industry and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs	77,847	77,847	77,847	77,847	77,847	77,847
R-squared	0.490	0.490	0.489	0.489	0.489	0.489

Notes: This table presents estimates from regressions of firm-year-level returns to 20 years of experience on firm characteristics. The reference group is non-exporters. Because unit prices are not directly comparable across products, we first compute firms' unit prices of products relative to average unit prices of exports to Argentina (which is of similar development levels to Brazil) for each 8-digit product and year. We then use export volume as weights to compute a weighted average unit price of exports for each firm and year. Controls: average years of schooling; share of workers with high-school degree; share of occupations intensive in cognitive tasks; share of production workers; average worker age; firm employment; and firm employment percentiles (divided into 10 bins) within each industry-year bin. Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%. *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

Table D.8: Wage Profiles and Firm Characteristics

	Dep Var: Firm-year-level Returns to 20 Yrs of Experience					
	(1)	(2)	(3)	(4)	(5)	(6)
	manufacturing					
	differentiated	non-differentiated	female	prod worker	nonprod worker	agri & mining
Period	94–10	94–10	94–10	94–10	94–10	94–10
Exporter	-0.004	-0.024	-0.100	0.003	0.007	0.284
	(0.055)	(0.046)	(0.069)	(0.041)	(0.078)	(0.188)
Exporter × ratio of #high-income to #total dests	0.251***	0.044	0.182**	0.114*	0.042	-0.221
	(0.084)	(0.067)	(0.087)	(0.059)	(0.101)	(0.226)
Exporter × log(#total dests)	-0.001	-0.013	0.031	0.006	0.002	-0.016
	(0.032)	(0.026)	(0.036)	(0.022)	(0.040)	(0.100)
Industry, Year and Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs	153,651	189,537	149,332	267,358	81,329	87,035
R-squared	0.337	0.334	0.329	0.322	0.353	0.309

Notes: This table presents regressions of firm-year-level returns to 20 years of experience on firm characteristics. The reference group is non-exporters. Controls: average years of schooling; share of workers with high-school degree; share of occupations intensive in cognitive tasks; share of production workers; average worker age; firm employment; and firm employment percentiles (divided into 10 bins) within each industry-year bin. Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%. *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms in Columns (1)–(5) and agricultural and mining firms in Column (6).

Table D.9: Wage Profiles and Control Variables

	Dep Var: Firm-year-level Returns to 20 Yrs of Experience									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Sample period	94–10	94–10	94–10	94–10	94–10	94–10	94–10	94–10	94–10	94–10
Exporter	-0.015	-0.017	-0.014	-0.007	-0.016	-0.009	-0.021	-0.009	-0.023	-0.037
	(0.035)	(0.035)	(0.035)	(0.036)	(0.035)	(0.040)	(0.036)	(0.035)	(0.042)	(0.045)
Exporter ×	0.134***	0.131***	0.138***	0.140***	0.134***	0.136**	0.142***	0.138***	0.168**	0.119*
ratio of #high-income to #total dests	(0.052)	(0.052)	(0.053)	(0.056)	(0.052)	(0.063)	(0.054)	(0.053)	(0.071)	(0.064)
Average years of schooling ×		0.021								
ratio of #high-income to #total dests		(0.022)								
Share of high-school graduates ×			-0.092							
ratio of #high-income to #total dests			(0.200)							
Average workers' age × ratio of				-0.011						
#high-income to #total dests				(0.016)						
Share of production workers × ratio of					-0.109					
#high-income to #total dests					(0.228)					
Share of managers × ratio of						-0.035				
#high-income to #total dests						(0.680)				
Share of marketing workers × ratio of							0.302			
#high-income to #total dests							(0.550)			
Share of occupations intensive in cognitive tasks								-0.039		
×ratio of #high-income to #total dests								(0.266)		
Log firm employment × ratio of									-0.044	
#high-income to #total dests									(0.042)	
Firm employment percentile (0–10%) ×										0.616
ratio of #high-income to #total dests										(0.750)
Firm employment percentile (10–20%) ×										-0.294
ratio of #high-income to #total dests										(0.729)
Firm employment percentile (20–30%) ×										-0.212
ratio of #high-income to #total dests										(0.427)
Firm employment percentile (30–40%) ×										-0.451
ratio of #high-income to #total dests										(0.318)
Firm employment percentile (40–50%) ×										-0.300
ratio of #high-income to #total dests										(0.264)
Firm employment percentile (50–60%) ×										0.128
ratio of #high-income to #total dests										(0.225)
Firm employment percentile (60–70%) ×										-0.125
ratio of #high-income to #total dests										(0.169)
Firm employment percentile (70–80%) ×										0.145
ratio of #high-income to #total dests										(0.140)
Firm employment percentile (80–90%) ×										0.074
ratio of #high-income to #total dests										(0.105)
Industry and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	344,658	344,658	344,658	344,658	344,658	344,658	344,658	344,658	344,658	344,658
R-squared	0.319	0.319	0.319	0.319	0.319	0.319	0.319	0.319	0.319	0.319

Notes: This table presents estimates from regressions of firm-year-level returns to 20 years of experience on firm characteristics. Controls: average years of schooling; share of workers with high-school degree; share of occupations intensive in cognitive tasks; share of production workers; average worker age; firm employment; and firm employment percentiles (divided into 10 bins) within each industry-year bin. Due to the space constraint, we do not report the coefficient on the interaction between the control variable and the exporter dummy, which is statistically insignificant in all scenarios. We also control for the levels of control variables when the corresponding interaction term is included. The reference group is non-exporters in the upper 10% of firm employment distribution within each industry-year. Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%. *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

Table D.10: Difference in Observables in Period Prior to Entry into High-income Destinations

	Treated Group	Control Group	Difference	t-statistic
Average Years of Schooling	8.551 (1.992)	8.582 (2.052)	-0.031 (0.046)	-0.67
Share of high-school grads	0.270 (0.226)	0.276 (0.237)	-0.006 (0.005)	-1.23
Average workers' age	32.143 (2.892)	32.232 (2.957)	-0.089 (0.066)	-1.35
Share of production workers	0.743 (0.214)	0.738 (0.221)	0.005 (0.005)	1.02
Share of occupations intensive in cognitive tasks	0.240 (0.195)	0.246 (0.200)	-0.006 (0.004)	-1.29
Log firm employment	4.841 (1.043)	4.831 (1.043)	0.010 (0.024)	0.42
Returns to 20 yrs of experience	0.952 (3.246)	0.953 (3.157)	0.000 (0.073)	0.00
Export status to non-high-income destinations	0.496 (0.500)	0.494 (0.500)	0.002 (0.011)	0.15

Notes: This table reports the t-tests between the chosen control group and the export entrants, for all the observables used in constructing the export probability in the matching estimator. Standard errors are in parentheses. *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

Table D.11: Returns to 20 Yrs of Experience at New Exporters to High-income Destinations

Post-exporting period	0	1	2	3
(a) Outcome: returns to experience				
Export entry	0.238***	0.266***	0.260**	0.187
	(0.082)	(0.099)	(0.104)	(0.117)
Nr treated	4,115	2,175	1,678	1,466
Nr controls	152,795	115,817	91,772	73,950
(b) Outcome: growth in returns (relative to $\tau = -1$ period)				
Export entry	0.238**	0.200	0.238	0.150
	(0.113)	(0.145)	(0.160)	(0.176)

Notes: The table reports the difference of returns to experience and growth in returns (relative to $\tau = -1$ period) between new exporters and non-exporters. The propensity score is estimated based on a Probit model, including a host of pre-exporting (previous year) firm characteristics: 1) average years of schooling; 2) share of workers with high-school degree; 3) share of occupations intensive in cognitive tasks; 4) share of production workers; 5) average worker age; 6) firm employment; 7) firm employment percentiles (divided into 10 bins) within each industry-year bin; 8) returns to 20 years of experience; and 9) export status to non-high-income destinations. We also control for industry and year fixed effects. The number of the treated and the control units on the common support decreases as there are fewer firms with future returns to experience. Standard errors are in parentheses. Significance levels: * 10%, ** 5%, *** 1%. *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

Table D.12: Returns to 20 Years of Experience at New Exporters to High-income Destinations

Post-exporting period	1	2	3
(a) Outcome: returns to experience			
Export entry	0.038	-0.144	0.080
	(0.120)	(0.103)	(0.103)
Nr treated	1,460	1,545	1,410
Nr controls	105,627	92,405	73,777
(b) Outcome: growth in returns (relative to $\tau = -1$ period)			
Export entry	0.000	-0.003	-0.175
	(0.167)	(0.159)	(0.162)

Notes: The table reports the difference of returns to experience and growth in returns (relative to $\tau = -1$ period) between export entrants that stop exporting in the corresponding period and non-exporters. The propensity score is estimated based on a Probit model, including a host of pre-exporting (previous year) firm characteristics: 1) average years of schooling; 2) share of workers with high-school degree; 3) share of occupations intensive in cognitive tasks; 4) share of production workers; 5) average worker age; 6) firm employment; 7) firm employment percentiles (divided into 10 bins) within each industry-year bin; 8) returns to 20 years of experience; and 9) export status to non-high-income destinations. We also control for industry and year fixed effects. The number of the treated and the control units on the common support decreases with post-exporting periods as there are fewer firms with future returns to experience. Standard errors are in parentheses. Significance levels: * 10%, ** 5%, *** 1%. *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

Table D.13: Returns to 20 Years of Experience at New Exporters to Non-high-income Destinations

Post-exporting period	0	1	2	3
(a) Outcome: returns to experience				
Export entry	0.078	-0.018	-0.016	0.014
	(0.078)	(0.099)	(0.106)	(0.110)
Nr treated	4,608	2,619	2,061	1,757
Nr controls	131,248	98,959	76,805	60,459
(b) Outcome: growth in returns (relative to $\tau = -1$ period)				
Export entry	0.060	-0.029	0.009	-0.113
	(0.112)	(0.142)	(0.159)	(0.163)

Notes: The table reports the difference of returns to experience and growth in returns (relative to $\tau = -1$ period) between new exporters and non-exporters. The propensity score is estimated based on a Probit model, including a host of pre-exporting (previous year) firm characteristics: 1) average years of schooling; 2) share of workers with high-school degree; 3) share of occupations intensive in cognitive tasks; 4) share of production workers; 5) average worker age; 6) firm employment; 7) firm employment percentiles (divided into 10 bins) within each industry-year bin; 8) returns to 20 years of experience; and 9) export status to high-income destinations. We also control for industry and year fixed effects. The number of the treated and the control units on the common support decreases with post-exporting periods as there are fewer firms with future returns to experience. Standard errors are in parentheses. Significance levels: * 10%, ** 5%, *** 1%. *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

Table D.14: Wage Change for 20 Years of Experience

Dep Var: Firm-year-level Log Hourly Wage Increase Time	(1) 1998-2000	(2) 1997-2001	(3) 1996-2002
Exporter × DV	-0.033	-0.102	-0.067
	(0.133)	(0.094)	(0.074)
Exporter$_{PRE}$ × DV	0.352	-0.049	-0.106
	(0.273)	(0.183)	(0.139)
Exporter × (1-DV)	0.279	-0.079	-0.017
	(0.248)	(0.147)	(0.105)
Ratio of #high-income dests to #total dests × DV	0.371*	0.285**	0.263**
	(0.194)	(0.140)	(0.111)
Ratio of #high-income dests to #total dests$_{PRE}$ × DV	0.272	0.270	0.214
	(0.440)	(0.289)	(0.217)
Ratio of #high-income dests to #total dests × (1-DV)	0.435	0.385*	0.191
	(0.387)	(0.229)	(0.160)
Year, industry and firm FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Obs	59,721	100,393	142,278
R-squared	0.604	0.486	0.412

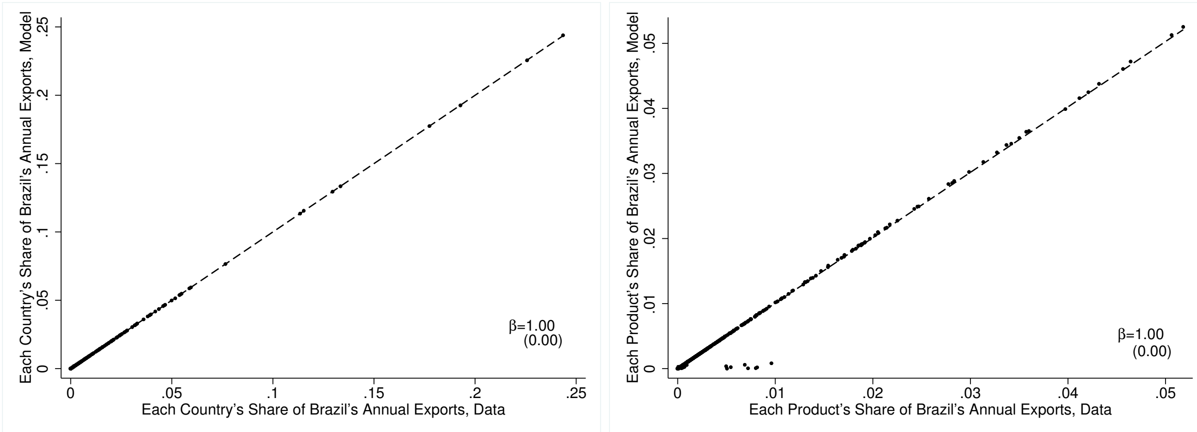
Notes: This table presents estimates from equation (D.2). The dependent variable is firm-year-level returns to 20 years of experience. The regression includes firm, industry, and year fixed effects. Controls: average years of schooling; share of workers with high-school degree; share of occupations intensive in cognitive tasks; share of production workers; average worker age; firm employment; and firm employment percentiles (divided into 10 bins) within each industry-year bin. Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%. *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

Table D.15: Wage Determinants

Dependent Variable: Log Hourly Wage (Current Year)	All Young Workers (1)	(2)	(3)	Displaced Young Workers (4)	(5)	(6)
Schooling	-0.001***	0.001***	-0.001***	0.059***	0.059***	0.059***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Schooling × Exporter	0.003***	0.003***	0.003***	0.023***	0.023***	0.023***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Exporter	-0.018***	-0.022***	-0.018***	-0.227***	-0.228***	-0.226***
	(0.001)	(0.001)	(0.001)	(0.016)	(0.016)	(0.016)
Years of working at exporters	0.098***	0.069***	0.096***	0.079***	0.082***	0.084***
(1–5 years of work history)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Years of working at non-exporters	0.085***	0.059***	0.085***	0.057***	0.061***	0.057***
(1–5 years of work history)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Years of working at exporters	0.050***	0.030***	0.049***	0.052***	0.052***	0.049***
(6–10 years of work history)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Years of working at non-exporters	0.042***	0.027***	0.042***	0.033***	0.034***	0.033***
(6–10 years of work history)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Years of working at exporters	0.031***	0.016***	0.030***	0.041***	0.038***	0.034***
(11–15 years of work history)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)
Years of working at non-exporters	0.027***	0.013***	0.027***	0.021***	0.021***	0.020***
(11–15 years of work history)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.002)
Years of working at exporters	0.024***	0.011***	0.024***	0.020***	0.021***	0.019***
(16–20 years of work history)	(0.001)	(0.001)	(0.001)	(0.002)	(0.004)	(0.006)
Years of working at non-exporters	0.019***	0.006***	0.019***	0.004	0.009*	0.003
(16–20 years of work history)	(0.001)	(0.001)	(0.001)	(0.005)	(0.006)	(0.005)
Years of working at exporters (1–5 years)		0.030***			0.029***	
& in same firm as current firm		(0.001)			(0.003)	
Years of working at exporters (1–5 years)			0.005***			-0.010***
× ratio of #high-income dests			(0.001)			(0.002)
Years of working at exporters (6–10 years)		0.025***			0.015***	
& in same firm as current firm		(0.001)			(0.003)	
Years of working at exporters (6–10 years)			0.003***			0.009***
× ratio of #high-income dests			(0.001)			(0.003)
Years of working at exporters (11–15 years)		0.019***			0.024***	
& in same firm as current firm		(0.001)			(0.005)	
Years of working at exporters (11–15 years)			0.005***			0.019***
× ratio of #high-income dests			(0.001)			(0.006)
Years of working at exporters (16–20 years)		0.015***			0.026**	
& in same firm as current firm		(0.001)			(0.011)	
Years of working at exporters (16–20 years)			0.001**			0.005
× ratio of #high-income dests			(0.001)			(0.012)
Year and firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Worker FE	Yes	Yes	Yes	No	No	No
Observations	34,072,713	34,072,713	34,072,713	255,211	255,211	255,313
R^2	0.878	0.880	0.878	0.665	0.666	0.663

Notes: The coefficients on the exporter dummy are the average difference of the time effects between exporters and non-exporters. We do not report the returns to 21–25 years of experience, for which there are few observations and thus the estimates are noisy. Due to the space constraints, we also do not report the coefficients on the years of working at non-exporters in the same firm as the current firm in Columns (2) and (5). We also control for industry effects and firm-year-level workforce characteristics (for the firm hiring the worker): 1) average years of schooling; 2) share of workers with high-school degree; 3) share of occupations intensive in cognitive tasks; 4) share of production workers; 5) average worker age; 6) firm employment; and 7) firm employment percentiles (divided into 10 bins) within each industry-year bin. Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%. *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

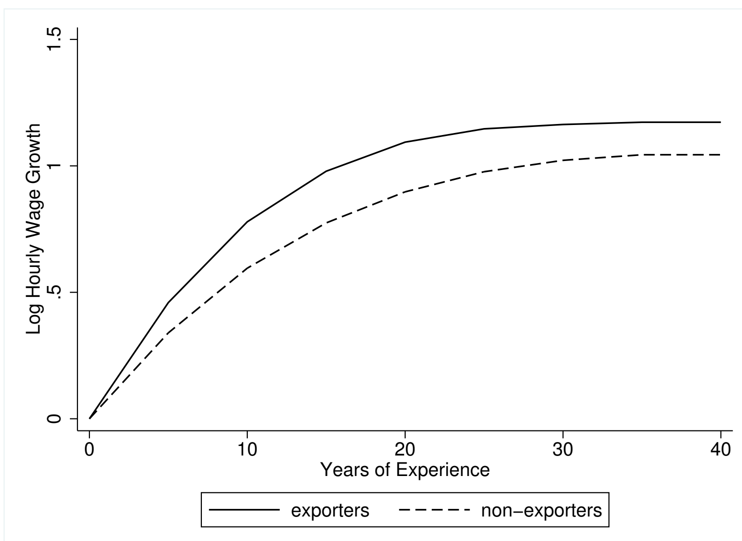
Figure D.2: Check of Customs Data with Official Reported Data, 97–00



(a) Exports by Country **(b)** Exports by 8-digit Products

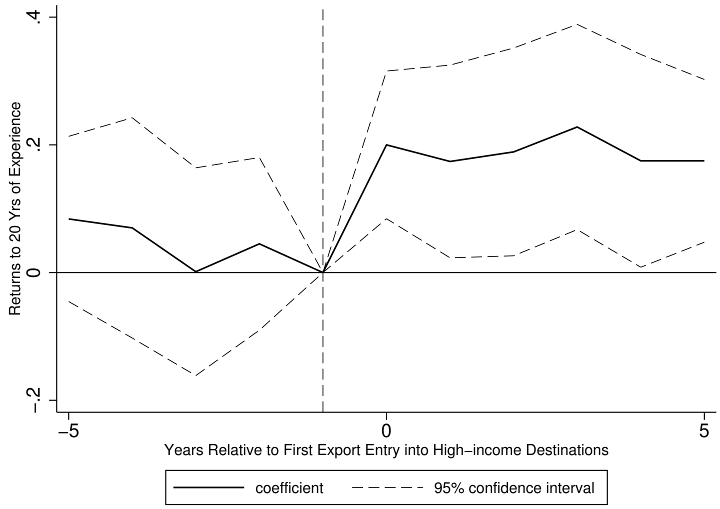
Notes: This graph compares each country's (product's) share of Brazilian annual exports between our SECEX customs data and the officially reported data from the Brazilian Ministry of Economy (Ministério da Economia). We pool the different years' shares together in the graph.

Figure D.3: Log Hourly Wage Increase by Exporters and Non-exporters



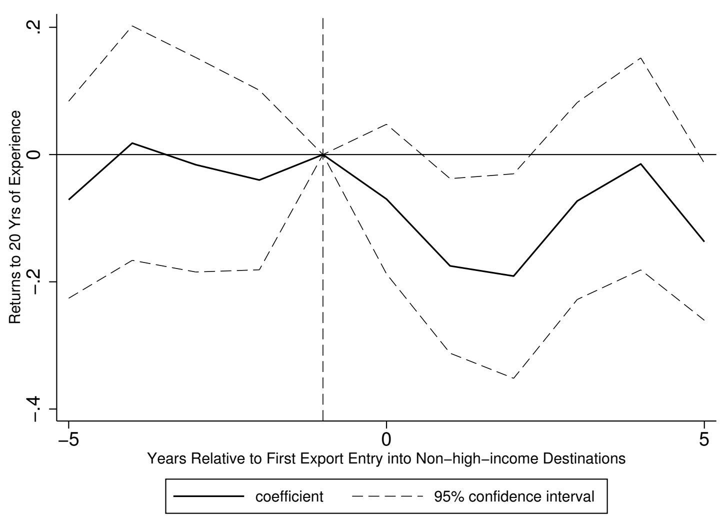
Notes: This figure presents the experience-wage profiles for workers at exporters and non-exporters, from estimating equation (1) using the Brazilian data between 1994–2010. We assume the final 5 years with no experience returns. *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

Figure D.4: Dynamics of Firms' First Entry Into High-income Destinations



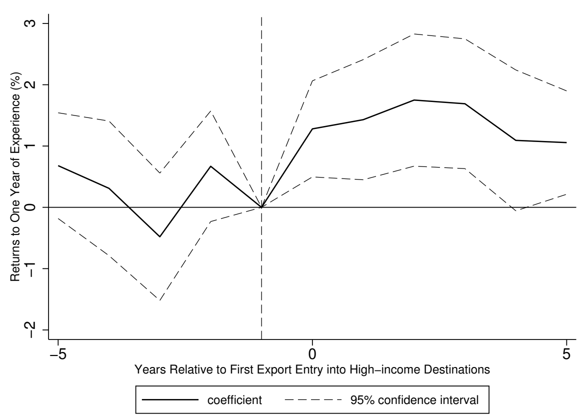
Notes: The figure shows the β_τ parameters from estimating equation (D.1). The dependent variable is firm-year-level returns to 20 years of experience. The regression controls for firm fixed effects, industry fixed effects, year fixed effects, and a dummy variable indicating whether the firm is exporting to a non-high-income destination. Other controls: average years of schooling; share of workers with high-school degree; share of occupations intensive in cognitive tasks; share of production workers; average worker age; firm employment; and firm employment percentiles (divided into 10 bins) within each industry-year bin. To estimate the β_τ parameters after entry, we require that firms remain exporting to high-income destinations. *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

Figure D.5: Dynamics of Firms' First Entry Into Non-high-income Destinations

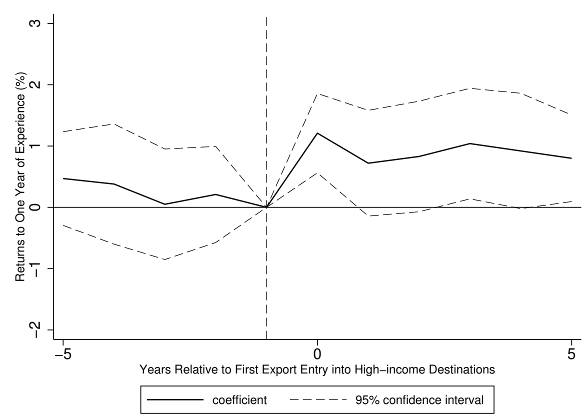


Notes: The figure shows the β_τ parameters from estimating equation (D.1), except for that the β_τ parameters are coefficients on indicators for time periods relative to the firm's first export entry into non-high-income destinations. The dependent variable is firm-year-level returns to 20 years of experience. The regression controls for firm fixed effects, industry fixed effects, year fixed effects, and a dummy variable indicating whether the firm is exporting to a high-income destination. Other controls: average years of schooling; share of workers with high-school degree; share of occupations intensive in cognitive tasks; share of production workers; average worker age; firm employment; and firm employment percentiles (divided into 10 bins) within each industry-year bin. To estimate the β_τ parameters after entry, we require that firms remain exporting to non-high-income destinations. *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

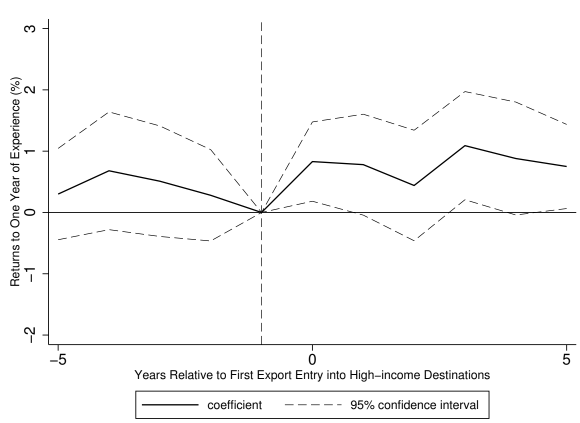
Figure D.6: Returns to One Year of Experience Across Different Experience Bins



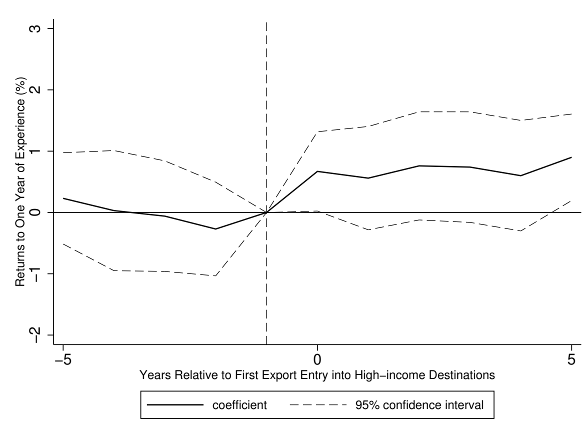
(a) Workers with 1–5 Years of Experience



(b) Workers with 6–10 Years of Experience



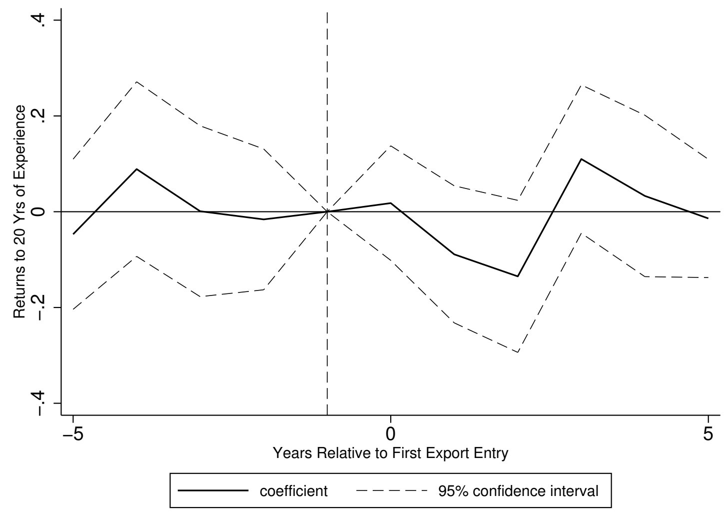
(c) Workers with 10–15 Years of Experience



(d) Workers with 16–20 Years of Experience

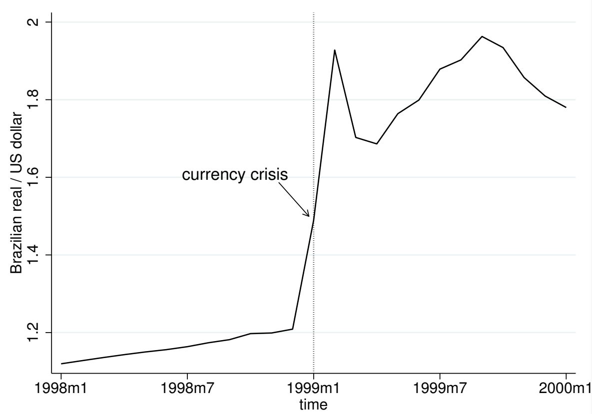
Notes: Parameters β_τ from estimating equation (D.1). The dependent variable is firm-year-level returns to one year of experience in the corresponding experience bin. Controls: firm fixed effects, industry fixed effects, year fixed effects, and an indicator for exports to a non-high-income destination. Other controls: average years of schooling; share of workers with high-school degree; share of occupations intensive in cognitive tasks; share of production workers; average worker age; firm employment; and firm employment percentiles (divided into 10 bins) within each industry-year bin. To estimate the β_τ parameters after entry, we require that firms remain exporting to high-income destinations. *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

Figure D.7: Dynamics of Firms' First Export Entry

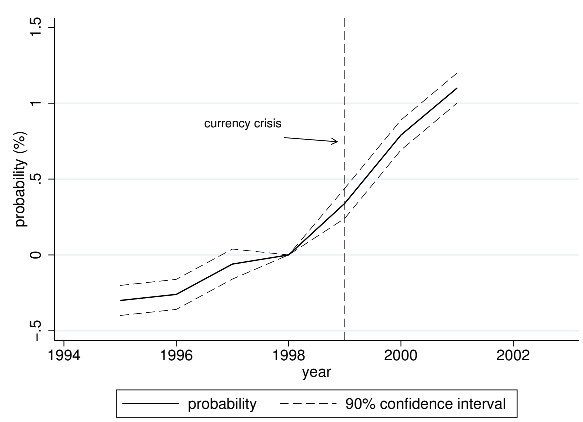


Notes: The figure shows the β_τ parameters from estimating equation (D.1), except for that the β_τ parameters are coefficients on indicators for time periods relative to the firm's first export entry. The dependent variable is firm-year-level returns to 20 years of experience. The regression controls for firm fixed effects, industry fixed effects, and year fixed effects. Other controls: average years of schooling; share of workers with high-school degree; share of occupations intensive in cognitive tasks; share of production workers; average worker age; firm employment; and firm employment percentiles (divided into 10 bins) within each industry-year bin. To estimate the β_τ parameters after entry, we require that firms remain exporting. *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

Figure D.8: Brazil Currency Crisis and Exporting Probability



(a) Brazil Currency Crisis



(b) Exporting Probability

Notes: Panel (a) presents the monthly Brazilian nominal exchange rates (per U.S. dollar), which are drawn from https://fxtop.com/. Panel (b) presents the probability of a firm exporting in each year. To obtain the probability, we regress the dummy variable of the export status (1, if the firm exports, and otherwise 0) on firm fixed effects, industry fixed effects, and year fixed effects. We plot the coefficients on year effects relative to 1998 (the baseline year) in Panel (b). *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

E Additional Theoretical Results

E.1 Learning Function

The learning function (6)

$$\phi^E(\omega) = \mu\, z(\omega)^{\gamma_1}\, \phi^O(\omega)^{\gamma_2}$$

is a key component of our model. The following considerations motivate the specification.

Workers can build knowledge by learning from colleagues, through on-site training or through learning-by-doing, and these opportunities are more easily available at firms with more advanced technology (e.g., Arrow, 1962; Hopenhayn and Chari, 1991). Thus, we directly model the dependence of learning returns on firm productivity, similar to the recent literature (e.g., Monge-Naranjo, 2019; Engbom, 2022). Learning also happens through interactions with the external environment. Firms may adjust their product requirements for different destinations (Verhoogen, 2008; Manova and Zhang, 2012), and managers can get new ideas by learning from clients and competitors abroad (Buera and Oberfield, 2020). Gains from trade-induced technology diffusion are several times larger than the static gains from trade (e.g., Alvarez, Buera and Lucas, 2013; Perla, Tonetti and Waugh, 2015; Sampson, 2016; Buera and Oberfield, 2020).[18] It is therefore natural to conjecture that workers' human capital embodies trade-induced knowledge. The share of output sold to a destination is a proxy to the share of employees assigned to the destination, so we weigh the exposure to the destinations' knowledge by output shares.

[18] Alvarez, Buera and Lucas (2013) consider knowledge diffusion in the domestic market and find that the GDP gain of costless trade relative to autarky is several times larger when knowledge diffusion is considered. Sampson (2016) studies technology diffusion from incumbents to entrants under endogenous firm entry and exit and finds that the gains from faster technology diffusion due to trade openness are around two times the standard static gains from trade according to Arkolakis, Costinot and Rodríguez-Clare (2012). Accounting for incumbents' technology adoption decisions, Perla, Tonetti and Waugh (2015) detect only a slight change in the gains from trade because, in their model, gains are largely offset by increases in adoption costs. In a model calibrated to cross-country data, Buera and Oberfield (2020) find that the gains from trade more than double after introducing the diffusion of ideas between competitors.

E.2 Value of Employment and Job Value

Value of employment. For a worker in firm ω with piece rate r, the value can be written as:

$$
\begin{aligned}
V^a(r, h_i^a, \mathbf{x}(\omega)) = & \underbrace{r\tilde{z}(\omega)(h_i^a - s^a(h_i^a, \omega))}_{\text{current wage}} \\
& + \underbrace{\frac{(1-\kappa)(1-\lambda_E) + (1-\kappa)\lambda_E \int (1-\mathbf{1}_{\textit{useful}})\,\mathrm{d}F(z(\nu))}{1+\rho} V^{a+1}(r, h_i^{a+1}, \mathbf{x}'(\omega))}_{\text{next-period value if the job is not exogenously separated and there is no negotiation}} \\
& + \underbrace{\frac{\kappa(1-\lambda_U)}{1+\rho} V_U^{a+1}(h_i^{a+1})}_{\text{next-period value if job destructed and worker unemployed}} \\
& + \underbrace{\frac{\kappa\lambda_U}{1+\rho} \int V_U^{a+1}(h_i^{a+1}) + \beta\left[M^{a+1}(h_i^{a+1}, \mathbf{x}'(\nu)) - V_U^a(h_i^{a+1})\right]\,\mathrm{d}F(z(\nu))}_{\text{next-period value if job destructed and worker employed}} \\
& + \underbrace{\frac{(1-\kappa)\lambda_E}{1+\rho}(1-\beta) \int \mathbf{1}_{\textit{useful}}\left[\min\{M^{a+1}(h_i^{a+1}, \mathbf{x}'(\nu)), M^{a+1}(h_i^{a+1}, \mathbf{x}'(\omega))\}\right]\,\mathrm{d}F(z(\nu)}_{\text{next-period portion of option value if job not exogenously destructed and negotiation at current/poaching firm}} \\
& + \underbrace{\frac{(1-\kappa)\lambda_E}{1+\rho}\beta \int \mathbf{1}_{\textit{useful}}\left[\max\{M^{a+1}(h_i^{a+1}, \mathbf{x}'(\nu)), M^{a+1}(h_i^{a+1}, \mathbf{x}'(\omega))\}\right]\,\mathrm{d}F(z(\nu),}_{\text{next-period portion of job value if job not exogenously destructed and negotiation at current/poaching firm}} \\
\text{s.t.} \quad & \underbrace{h_i^{a+1} = (1-\delta_h)h_i^a + \phi^E(\omega)s^a(h_i^a, \omega)^\alpha}_{\text{human capital evolution}}, \quad \underbrace{\mathbf{x}'(\omega) = \Gamma(\mathbf{x}(\omega))}_{\text{law of motion for firm's state}} \; . \qquad \text{(E.1)}
\end{aligned}
$$

The specification $V^a(r, h_i^a, \mathbf{x}(\omega))$ shows that workers' value relies on four sets of state variables—age, contractual piece rate, human capital stock, and employer's state.[19] $\mathbf{1}_{\textit{useful}}$ is a dummy variable that indicates a useful poaching offer to the worker and takes the value of one if $M^{a+1}(h_i^{a+1}, \mathbf{x}'(\nu)) > V^{a+1}(r, h_i^{a+1}, \mathbf{x}'(\omega))$, so that there is either a renegotiation with the current firm or a negotiation with the poaching firm. The first and second lines of the equation capture the current wage, as well as the future value if the worker is not exogenously separated and does not face an attractive outside offer in the next period. The third and fourth lines show the future value if the worker is exogenously separated from the firm, which happens with a probability κ. In this case, the worker enjoys the unemployment value or obtains a higher value if she can find a job immediately. Finally, the remaining lines capture the future value if poaching happens with an attractive offer to the worker. As described earlier, there are two scenarios: (1) the current job continues, and the worker renegotiates with the current firm; or (2) the worker moves to the poaching firm and negotiates with the poaching firm. In either scenario, the worker uses the value of the less valuable job, $\min\{M^{a+1}(h_i^{a+1}, \mathbf{x}'(\nu)), M^{a+1}(h_i^{a+1}, \mathbf{x}'(\omega))\}$ as the outside option to negotiate a new rate r' in the more valuable job, and with the new piece rate r', the value of employment is a weighted average of the job values at the current firm and the poaching firm.

As discussed in the main text, we assume that unemployment is equivalent to employment in

[19] We focus on steady state, so we omit aggregate state variables from $V^a(r, h_i^a, \mathbf{x}(\omega))$.

the least productive firm: $V_U^a(h_i^a) = \min_\omega M^a(h_i^a, \mathbf{x}(\omega))$.

Job value. For a worker-firm match, the job value is given by:

$$\begin{aligned}
M^a(h_i^a, \mathbf{x}(\omega)) = & \underbrace{\tilde{z}(\omega)(h_i^a - s^a(h_i^a, \omega))}_{\text{current revenue}} \\
& + \underbrace{\frac{(1-\kappa)(1-\lambda_E) + (1-\kappa)\lambda_E \int (1 - \mathbf{1}_{move})\, \mathrm{d}F(z(\nu))}{1+\rho} M^{a+1}(h_i^{a+1}, \mathbf{x}'(\omega))}_{\text{next-period value if the job continues}} \\
& + \underbrace{\frac{\kappa(1-\lambda_U)}{1+\rho} V_U^{a+1}(h_i^{a+1})}_{\text{next-period value if job exogenously destructed and worker unemployed}} \\
& + \underbrace{\frac{\kappa\lambda_U}{1+\rho}\left(V_U^{a+1}(h_i^{a+1}) + \int \beta[M^{a+1}(h_i^{a+1}, \mathbf{x}'(\nu)) - V_U^a(h_i^{a+1})]\, \mathrm{d}F(z(\nu))\right)}_{\text{next-period value if job exogenously destructed and worker employed}} \\
& + \underbrace{\frac{(1-\kappa)\lambda_E}{1+\rho} \int \mathbf{1}_{move}\left[M^{a+1}(h_i^{a+1}, \mathbf{x}'(\omega)) + \beta\left(M^{a+1}(h_i^{a+1}, \mathbf{x}'(\nu)) - M^{a+1}(h_i^{a+1}, \mathbf{x}'(\omega))\right)\right] \mathrm{d}F(z(\nu))}_{\text{next-period value if worker moves to poaching firm}}, \\
\text{s.t.} \quad & \underbrace{h_i^{a+1} = (1-\delta_h)h_i^a + \phi^E(\omega)s^a(h_i^a, \omega)^\alpha}_{\text{human capital evolution}}, \quad \underbrace{\mathbf{x}'(\omega) = \Gamma(\mathbf{x}(\omega))}_{\text{law of motion for firm's state}} .
\end{aligned} \tag{E.2}$$

$\mathbf{1}_{move}$ is a dummy variable indicating a job-to-job move.[20] The first and second lines capture the production value in the current period, as well as the next-period job value if the worker stays in the firm. The third and fourth lines show the future value of employment if the job is exogenously destructed. In this case, the worker enjoys the unemployment value and may find a job immediately. Finally, the last line captures the future value if the worker moves to a poaching firm. The worker will use the current job's value as an outside option and get an extra surplus as the poaching firm values the worker better.

E.3 Vacancy Choices

The optimal amount of vacancies $v(\omega)$ posted by firm ω is determined as:

$$\begin{aligned}
c_v v(\omega)^{\gamma_v} P_1 = & \sum_a \frac{\lambda_U(1-\beta)}{V} \int [M^a(h^a, \mathbf{x}(\omega)) - V_U^a(h^a)]\, D_U^a(h^a)\, \mathrm{d}h^a \\
& + \sum_a \frac{\lambda_E(1-\beta)}{V} \int\int \max\{M^a(h^a, \mathbf{x}(\omega)) - M^a(h^a, \mathbf{x}(\nu)), 0\} D^a(h^a, \nu)\, \mathrm{d}h^a\, \mathrm{d}\Phi(z(\nu)).
\end{aligned} \tag{E.3}$$

[20]This happens if $M^{a+1}(h_i^{a+1}, \mathbf{x}'(\nu)) > M^{a+1}(h_i^{a+1}, \mathbf{x}'(\omega))$, which means that the poaching firm's job is more valuable than the current job.

Here $D_U^a(h^a)$ is the measure of unemployed workers with human capital h^a, and $D^a(h^a,\omega)$ is the measure of employed workers with human capital h^a and at firm ω.[21] The left-hand side captures the marginal costs of posting a vacancy. The right-hand side captures the aggregate value per vacancy from hiring unemployed workers and poaching employed workers from other firms, with $(1-\beta)$ governing the firm's share of the increment in surplus from hiring.

E.4 Definition of Equilibrium

Now we define the general equilibrium of our model as follows:

Definition 1 *The general equilibrium consists of meeting rates $\{\lambda_E, \lambda_U\}$, employment distributions $\{D_U^a(h^a), D^a(h^a,\omega)\}$, firms' export destinations and revenues $\{y_n(\omega), \tilde{z}(\omega)\}$ and vacancy posting $v(\omega)$, the law of motion for a firm's state $\Gamma(\mathbf{x}(\omega))$, the worker-firm joint decision of human capital accumulation $s^a(h_i^a,\omega)$, each worker's piece rate $r_i(\omega)$, and aggregate price and quantity variables in the home country $\{P_1, Y_1\}$. These variables satisfy:*
(1) each worker's piece rate $r_i(\omega)$ satisfies the bargaining processes specified in Section III.B;
(2) the worker-firm joint decision of human capital accumulation $s^a(h_i^a,\omega)$ is given by equation (9), which maximizes the job value specified by equation (E.2);
(3) firms' export destinations and revenues $\{y_n(\omega), \tilde{z}(\omega)\}$ are given to maximize the benefit in equation (10), given employment distributions and aggregate price and quantities, and the perceived law of motion for firms' state $\mathbf{x}'(\omega) = \Gamma(\mathbf{x}(\omega))$ is consistent with actual transition of firms' state over time;
(4) firms' optimal vacancy postings $v(\omega)$ are given by equation (E.3);
(5) meeting rates $\{\lambda_E, \lambda_U\}$ are determined by unemployment rate $U = \sum_a \int D_U^a(h^a)\, dh^a$ and the total amount of vacancies $V = \bar{M} \int v(\omega)\, d\Phi(z(\omega))$;
(6) employment distributions $\{D_U^a(h^a), D^a(h^a,\omega)\}$ are consistent with revenues $\tilde{z}(\omega)$, vacancies $v(\omega)$, and the worker-firm joint decision of human capital accumulation $s^a(h_i^a,\omega)$ across all workers within the firm $i \in \mathbb{I}(\omega)$; and
(7) aggregate price and quantity $\{P_1, Y_1\}$ clear the goods market in the home country.

E.5 Decomposition of Gains from Trade

A further question is whether the impact of export activity on wage profiles matters for the aggregate economy. The following proposition characterizes the gains from trade, which are defined as changes in the real income (domestic firms' total production value divided by the final-good price) from autarky to the observed economy.

Proposition 1 *Suppose that meeting and separation rates $\lambda_U = 1$ and $\kappa = 1$, unemployment value $V_U^a(h_i^a) = 0\ \forall\ i, a,$[22] discount rate ρ is large enough, and vacancy costs are linear $\gamma_v = 0$. The*

[21] We define $D_U^a(h^a)$ and $D^a(h^a,\omega)$ at the time point after exogenous job separations but before job search. Thus, $\sum_a \int D_U^a(h^a)\, \mathrm{d}h^a = U$ and $\sum_a \int\int D^a(h^a,\nu)\, \mathrm{d}h^a\, \mathrm{d}\Phi(z(\nu)) = A - U$.

[22] This assumption can be justified by $z_{\text{min}} \to 0$ or disutility of unemployment (Hornstein et al., 2011), though in the current model's quantitative analysis, we abstract from directly modeling the unemployment disutility by following Bagger et al. (2014) to conveniently assume that the unemployment value is equivalent to the employment value in the least productive firm, as discussed in Section III.B.

gains from trade are:

$$GT = \underbrace{\Pi_d^{-\frac{1}{\sigma-1}}}_{\text{changes in real income per efficiency labor}} \times \underbrace{\frac{\bar{h}}{\bar{h}^{aut}}}_{\text{changes in average efficiency labor per employee}} . \tag{E.4}$$

Π_d is the home-country expenditure share on domestic goods in the observed economy. $\bar{h}$ and $\bar{h}^{aut}$ denote the average human capital level in the observed economy and the autarkic economy, respectively.

Proof: See Section E.6. □

We obtain Proposition 1 under several assumptions for analytical tractability. The meeting and separation rates $\lambda_U = 1$ and $\kappa = 1$ ensure full employment and that firms behave like hiring in a spot market in each period, which resembles the typical assumption in the Melitz model (Melitz, 2003).[23] The assumptions of unemployment value $V_U^a(h_i^a) = 0$ and large discount rate ρ imply that firms obtain a proportion $(1-\beta)$ of revenues, and that time spent on human capital accumulation is relatively little. The assumption of $\gamma_v = 0$ implies that marginal costs of hiring remain constant, and thus export decisions across destinations are independent. All these assumptions will be relaxed quantitatively, but as shown below, the formula in Proposition 1 still provides a good approximation of our quantitative result.

Proposition 1 decomposes the gains from trade into two components. The first component $\Pi_d^{-\frac{1}{\sigma-1}}$ reflects the gains due to changes in real income per efficiency labor after trade openness. This component is also a well-studied property of gravity equations that arise from a large number of micro-theoretical foundations with exogenous labor supply (e.g., Arkolakis, Costinot and Rodríguez-Clare, 2012; Costinot and Rodríguez-Clare, 2014).

The second component indicates how trade openness affects the average level of employees' efficiency labor. If the impact of export destinations on wage profiles partly reflects human capital accumulation, the resulting change in human capital of workers at exporters would produce aggregate welfare effects. Moreover, the typical Melitz force can also reinforce the gains in employees' average efficiency labor, as trade induces workers' reallocation toward exporters where workers may enjoy faster human capital accumulation.

In our calibrated model, if we directly apply the formula for the gains from trade in Proposition 1, the gains from trade are 7.73%, similar to the actual gains from trade in Table 3 (7.78%). This indicates that changes in human capital and real income per efficiency labor can account for most of the gains from trade, and therefore the formula in Proposition 1 provides a good approximation of our quantitative finding. Given that Proposition 1 is derived under strict assumptions on labor market frictions, Section F.5 provides a discussion of how strictly imposing such assumptions affects the gains in human capital from trade.

[23] Under the assumptions of Proposition 1, we abstract from wage renegotiations by letting all the workers be separated from firms in each period ($\kappa = 1$). Wage renegotiations occur in the more realistic case of $\kappa < 1$ and $\lambda_E > 0$, when some workers stay in the firm and derive outside offers from poaching firms. We will include the effects of wage renegotiations numerically.

E.6 Proof of Proposition 1

E.6.1 Optimal quantities sold to export destinations

The discount rate ρ is large enough, so the choice of export destinations does not depend on the future job value. We first solve the optimal quantities $\{y_n(\omega)\}$ given the extensive margin of export decisions $\{\mathbf{1}_{\{y_n(\omega)>0\}}\}$. For ease of notations, we define $I_n(\omega) = \mathbf{1}_{\{y_n(\omega)>0\}}$. Using equation (10), the problem becomes

$$\begin{aligned} &\max_{\{y_n\}} \sum_n I_n(\omega) \left(y_n(\omega)^{\frac{\sigma-1}{\sigma}} P_n Y_n^{\frac{1}{\sigma}} - P_1 f_n \right), \\ &s.t. \sum_n I_n(\omega) \tau_n y_n = z(\omega) h(\omega). \end{aligned} \tag{E.5}$$

We can redefine the problem as:

$$\max_{\{y_n(\omega)\}} \sum_n I_n(\omega) \left(y_n(\omega)^{\frac{\sigma-1}{\sigma}} P_n Y_n^{\frac{1}{\sigma}} - P_1 f_n \right) + \lambda \left(z(\omega) h(\omega) - \sum_n I_n(\omega) \tau_n y_n \right), \tag{E.6}$$

where λ is the Lagrange multiplier. The first-order conditions with regard to $\{y_n(\omega)\}$ and λ imply:

$$\begin{aligned} &I_n(\omega) \frac{\sigma-1}{\sigma} y_n(\omega)^{-\frac{1}{\sigma}} P_n Y_n^{\frac{1}{\sigma}} = \lambda I_n(\omega) \tau_n, \quad \forall\, n \\ &z(\omega) h(\omega) = \sum_n I_n(\omega) \tau_n y_n(\omega). \end{aligned}$$

Solving these first-order conditions leads to:

$$y_n(\omega) = \frac{I_n(\omega) P_n^{\sigma} Y_n \tau_n^{-\sigma}}{\sum_{n'=1}^{N} I_{n'}(\omega) P_{n'}^{\sigma} Y_{n'} \tau_{n'}^{1-\sigma}} z(\omega) h(\omega), \tag{E.7}$$

and the Lagrange multiplier λ (marginal revenue of output) is:

$$\lambda = \frac{\sigma-1}{\sigma} \left(\sum_{n'=1}^{N} I_{n'}(\omega) P_{n'}^{\sigma} Y_{n'} \tau_{n'}^{1-\sigma} \right)^{\frac{1}{\sigma}} (z(\omega) h(\omega))^{-\frac{1}{\sigma}}. \tag{E.8}$$

E.6.2 Optimal hires and export choices

Because unemployment benefits $V_U^a(h_i^a) = 0 \;\forall\, i, a$ and the discount rate ρ is large enough, firms obtain a fixed portion $(1-\beta)$ of total sales according to equation (E.2). According to equation (E.3):

$$(1-\beta) \frac{\sum_n I_n(\omega) y_n(\omega)^{\frac{\sigma-1}{\sigma}} P_n Y_n^{\frac{1}{\sigma}}}{h(\omega)} \frac{A}{V} \bar{h} = c_v P_1.$$

where $\frac{A}{V}$ is the number of hires per vacancy (recall A is the total population), and $\bar{h}$ is the average human capital of workers in the economy. Noting that $h(\omega) = \frac{v(\omega)}{V} A \bar{h}$. Combining this with equation (E.7) yields the optimal $v(\omega)$,

$$v(\omega) = (1-\beta)^{\sigma} \left(\sum_{n=1}^{N} I_n(\omega) P_n^{\sigma} Y_n \tau_n^{1-\sigma} \right) \left(\frac{z(\omega) A \bar{h}}{V} \right)^{\sigma-1} (c_v P_1)^{-\sigma} . \tag{E.9}$$

Combining this with equation (E.7), it is easy to see

$$y_n(\omega) = I_n(\omega) P_n^{\sigma} Y_n \tau_n^{-\sigma} (1-\beta)^{\sigma} \left(\frac{z(\omega) A \bar{h}}{V} \right)^{\sigma} (c_v P_1)^{-\sigma} . \tag{E.10}$$

If $I_n(\omega) = 1$, combining this with $p_n(\omega) = y_n(\omega)^{-\frac{1}{\sigma}} P_n Y_n^{\frac{1}{\sigma}}$, we obtain

$$p_n(\omega) = \frac{\tau_n c_v P_1 V}{(1-\beta) z(\omega) A \bar{h}}, \tag{E.11}$$

which resembles a Melitz-Chaney-type model with prices of production $\frac{c_v P_1 V}{(1-\beta) A \bar{h}}$ if $z(\omega) = 1$. Because workers capture a portion β of firms' revenue, workers' average wage at firm z is

$$\bar{w}_1 = \bar{w}_1(\omega) = \beta \bar{h} \frac{\sum_n I_n(z) p_n(\omega) y_n(\omega)}{h(\omega)} = \frac{\beta c_v P_1 V}{(1-\beta) A}, \tag{E.12}$$

which is identical across firms.

As shown in equation (E.10), under optimal choices of hires, the firm's optimal choice is independent of other destinations. Therefore, export decisions are made independently for each destination. A firm will export to destination n ($I_n(\omega) = 1$) if $p_n(\omega) y_n(\omega) \geq f_n P_1$.

E.6.3 Trade shares in the home market

Let Π_d denote the share of expenditures devoted to domestic goods in the home country. Because of marketing costs $f_1 = 0$, all domestic firms sell in the home country. Then, we can obtain:

$$\begin{aligned} \Pi_d &= \frac{\bar{M} \int_{z_{\min}}^{\infty} p_1(\omega)^{1-\sigma} \, \mathrm{d}\Phi(z(\omega))}{\bar{M} \int_{z_{\min}}^{\infty} p_1(\omega)^{1-\sigma} \, \mathrm{d}\Phi(z(\omega)) + \bar{M}^I (p^I)^{1-\sigma}} \\ &= \frac{\bar{M} \int_{z_{\min}}^{\infty} z(\omega)^{\sigma-1} \, \mathrm{d}\Phi(z(\omega)) \left(\frac{c_v P_1 V}{(1-\beta) A \bar{h}} \right)^{1-\sigma}}{\bar{M} \int_{z_{\min}}^{\infty} z(\omega)^{\sigma-1} \, \mathrm{d}\Phi(z(\omega)) \left(\frac{c_v P_1 V}{(1-\beta) A \bar{h}} \right)^{1-\sigma} + \bar{M}^I (p^I)^{1-\sigma}}, \end{aligned} \tag{E.13}$$

where we use equation (E.11). Note this is a standard gravity equation with trade elasticity $\sigma - 1$, as typically used in the trade literature (reviewed by Costinot and Rodríguez-Clare, 2014). And the price index in the home country is

$$P_1 = \left(\bar{M} \int_{z_{\min}^*}^{\infty} z(\omega)^{\sigma-1} \, \mathrm{d}\Phi(z(\omega)) \left(\frac{c_v P_1 V}{(1-\beta) A \bar{h}} \right)^{1-\sigma} + \bar{M}^I (p^I)^{1-\sigma} \right)^{\frac{1}{1-\sigma}} . \tag{E.14}$$

E.6.4 Gains from trade

Finally, we characterize the gains from trade. The real expenditure in the home country can be written as:

$$X_1 = \frac{A\bar{w}_1}{\beta P_1} = A(\Pi_d)^{-\frac{1}{\sigma-1}}\bar{h}\left(\bar{M}\int_{z^*_{\min}}^{\infty} z(\omega)^{\sigma-1}\,\mathrm{d}\Phi(z(\omega))\right)^{\frac{1}{\sigma-1}} \tag{E.15}$$

where $\frac{\bar{w}_1}{P_1}$ is real wage, A is the population size, and β is the ratio of wage payments to total revenues. We denote the variables in the autarkic economy with superscript aut. Note that $\Pi_d = 1$ in autarky. Then the gains from trade can be written as:

$$GT = \underbrace{\Pi_d^{-\frac{1}{\sigma-1}}}_{\text{changes in real income per efficiency labor}} \times \underbrace{\frac{\bar{h}}{\bar{h}^{aut}}}_{\text{changes in average efficiency labor per employee}}. \tag{E.16}$$

This step completes the proof.

E.7 Incorporating Learning-by-Doing

Instead of assuming endogenous choices of human capital investment, an alternative approach of incorporating human capital is to assume learning-by-doing: the human capital processes are exogenously given and can potentially vary across firms and ages (e.g., Bagger et al., 2014; Gregory, 2021). In particular, we assume that for a worker of age a at firm ω, the human capital growth is exogenously given by:

$$\phi^{E,a}(\omega) = \mu z(\omega)^{\gamma_1}\phi^{O}(\omega)^{\gamma_2}\exp(-\rho_h a). \tag{E.17}$$

Compared with our baseline model, we now assume: (1) there is no time needed for human capital accumulation, so that the time spent on human capital accumulation $s^a = 0$; and (2) to generate a reduction in learning speed in later ages, we introduce an additional parameter $\rho_h > 0$. We calibrate the newly introduced $\rho_h > 0$ together with other parameters (which are same as in the baseline model) to match the targeted moments. To match the new parameter ρ_h, we also introduce a new targeted moment—the returns to the first 5 years of workers' experience. The other targeted moments are the same as in Table F.1.

F Additional Quantitative Results

F.1 Computation Algorithm

The computation strategy of the model's calibration is as follows.

1. We first divide the productivity distribution into 500 equally sized bins according to the cumulative probability of the productivity distribution and then draw a firm from the middle point of each bin.

2. We then draw the random realization of export fixed costs for each firm and each destination. The realizations of export costs are fixed in the baseline equilibrium throughout the paper.

We also experimented with 50 different realizations for each firm and destination and then use the average simulation results to compute the model moments, and the results are very similar (though computationally cumbersome).

3. Given a set of parameters, we compute the baseline equilibrium. To compute moments regarding changes immediately following export entry, we implement a different realization of export fixed costs for each firm on the baseline equilibrium. As it is difficult to compute the full transitional dynamics, we focus on the immediate period of export entry with firms' employment distribution and aggregate variables being the same as in the baseline equilibrium. We compute how the changes (due to export entry) in labor productivity and the human capital increment per time spent affect experience effects. This is motivated by our estimated effects in Table D.11 that capture the short-run effects.[24] We search the internally calibrated parameters to minimize the absolute difference between the data moments and the model moments in the baseline equilibrium and regarding export entry.

F.2 Moments and Model Validation

Untargeted moments. In Table F.1, we compare several untargeted moments in the model to the data. Even though we did not directly target experience effects in the calibration, our model-generated differences in experience effects between exporters and non-exporters are similar to the data. Finally, our model predicts negative changes in experience effects due to export entry into non-high-income countries, in line with the reduced-form evidence in Table D.13.

Model validation. We use the enterprise survey (ES) for Brazil in 2009 to provide additional evidence on workers' human capital accumulation—the key model mechanism for the within-job wage profiles. The ES is a representative firm-level sample of an economy's private manufacturing and service firms surveyed by the World Bank. Consistent with our analysis of the RAIS data, we restrict the ES to manufacturing firms with at least 10 employees, with totally 1,140 firms in the sample.

The ES reports the share of workers that receive formal training and does not incorporate other forms of human capital accumulation (such as learning from supervisors). Despite the lack of a direct correspondence between the ES training data and our model, it is still a good exercise to check whether the (unit-free) elasticity of learning intensity to employment size is similar between the model and the data. As we cannot take the logarithm of the share of trained workers (many firms report 0%) in the ES, we divide firms (ranked by employment) into 50 equally sized bins and then regress the logarithm of the share of trained workers on log average firm size across bins. In the model, we divide the firm employment distribution into 50 equally sized bins and regress the logarithm of average time spent on human capital accumulation on log average firm size across bins.[25]

[24] Our algorithm is similar to the short-run partial-equilibrium analysis frequently used in the recent development literature (Buera et al., 2021b; Buera, Kaboski and Townsend, 2021) to incorporate the reduced-form evidence into a general-equilibrium analysis.

[25] In our model, all firms provide chances of human capital accumulation, and there is no extensive margin of human capital accumulation. In principle, we can also incorporate idiosyncratic fixed costs of human capital accumulation

Table F.1: Moments in the Model and the Data

Statistics	Target	Data	Model
Trade Statistics			
Share of exporters, by destination ($N = 2, ..., 10$)	$\surd$	0.032 (0.031)	0.032 (0.030)
Ratio of exports to firms' total sales, by destination ($N = 2, ..., 10$)	$\surd$	0.015 (0.023)	0.015 (0.022)
Ratio of imports to firms' total sales	$\surd$	0.14	0.14
Slope of num of export destinations on log firm employment	$\surd$	0.53	0.51
Labor Market Statistics			
Job finding rate (unemployed workers)	$\surd$	0.67	0.67
Vacancy filling rate	$\surd$	0.88	0.89
Share of workers that remain employed after one year	$\surd$	0.87	0.87
Share of new hires that were employed in other firms (last year)	$\surd$	0.51	0.51
Pareto parameter of firm employment distribution	$\surd$	1.03	1.21
Unemployment rate		0.08	0.08
Wage Levels			
Slope of wages on log firm employment	$\surd$	0.06	0.06
Exporter wage premium		0.11	0.06
Wage Profiles			
Slope of experience returns on firm size	$\surd$	0.15	0.15
Average experience returns (employment-weighted)	$\surd$	0.94	0.94
Average experience returns (unweighted)		0.73	0.80
Diff in average returns btw exporters/non-exporters (employment-weighted)		0.18	0.28
Diff in average returns btw exporters/non-exporters (unweighted)		0.27	0.22
Changes in returns after entry into high-income destinations	$\surd$	0.22	0.21
Changes in returns after entry into non-high-income destinations		-0.01	-0.12

Notes: The results for the share of exporters and the ratio of exports to firms' total sales refer to the average across all the foreign destinations, with the standard deviation in parentheses. We compute the trade statistics using the linked RAIS-customs data in 2000. The data on job finding rates and vacancy filling rates is from Dix-Carneiro et al. (2021), and the unemployment rate is from the World Bank. We compute the remaining labor market statistics using the RAIS data. Also using the RAIS data, we compute the exporter premium (the slope of wages on firm employment) by regressing log wage on the exporter dummy (log firm employment), individual fixed effects, and year fixed effects. Finally, we construct experience returns (to 20 years of experience) in the same way as in Section II.C. We compute exporters' (non-exporters') employment-weighted experience returns, by averaging experience returns across exporters (non-exporters), using each firm's employment as weights. Experience returns with regard to export entry are the average of reduced-form evidence in Tables D.11 and D.13 based on the propensity-matching estimator.

Table F.2 reports the results. The observed data and our model-generated data both predict more training in larger firms, even after controlling for the share of exporters. The elasticity of learning intensity to firm employment is smaller in our model than in the actual data. One possible reason for this difference is that small firms are more involved in informal training, whereas the ES only reports the formal training.[26]

across firms, and thus firms that enjoy larger benefits from human capital accumulation will also perform more of it in the extensive margin.

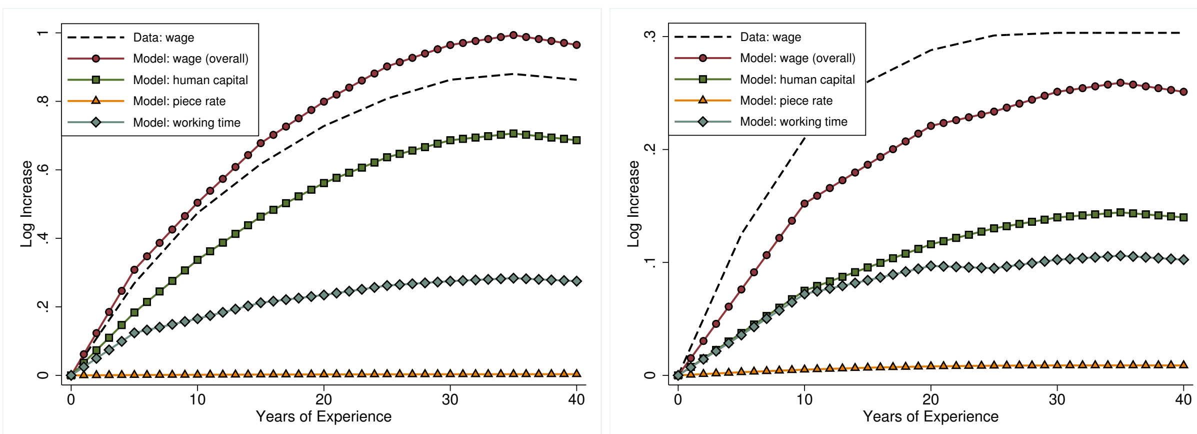
[26] For example, in the 1995 U.S. Survey on Employer-provided Training, firms with 50–99 employees only report 21% of their training time as formal training, whereas firms with 500+ employees report 40% of their training time as formal training.

Table F.2: Comparison of Model Results with Training Data

Dep Var	Log(% of trained workers)		Log(time on HC accumulation)	
	data	data	model	model
Log(avg firm employment)	0.209***	0.192***	0.104***	0.083***
	(0.029)	(0.062)	(0.010)	(0.025)
Share of exporters		0.116		0.045
		(0.380)		(0.049)
Obs	50	50	50	50
R-squared	0.626	0.626	0.839	0.844

Notes: As the households in the model are homogeneous in their initial skills, we also control for average workers' schooling in the ES data. There is no other information on labor composition (e.g., occupations) in the ES. Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%. *Data Sources*: the enterprise survey (ES) for Brazil in 2009.

Figure F.1: Decomposing the Returns to Experience



(a) Overall Experience-wage Profiles

(b) Difference btw Exporters/non-exporters

Notes: The data on experience returns are computed according to Section II.C. We report the (unweighted) average experience-wage profiles across firms in Figure F.1a and the (unweighted) average differences between exporters and non-exporters in Figure F.1b. *Data Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

F.3 Decomposing the Returns to Experience

With the calibrated model, we now turn to understanding what shapes experience-wage profiles. Figure F.1a presents the overall experience-wage profiles (averaged across firms) and decomposes them into different factors. Human capital accumulation accounts for about 70% of workers' overall wage growth over the life cycle. Figure F.1b shows that human capital is still an important factor behind the difference in workers' life-cycle wage growth between exporters and non-exporters. However, because of the diminishing returns of human capital investment, the contribution of human capital growth to explaining the difference (55%) is smaller than the role of human capital in explaining the overall wage profiles shown in Figure F.1a, whereas the contribution of changes in work time becomes larger.

Table F.3 presents the decomposition of changes in returns to experience due to export entry. We find that human capital accounts for half of the gains in experience returns after entry to

Table F.3: Changes in Returns to 20 Years of Experience due to Export Entry

	Data	Model	Model-based Decomposition: Human Capital	Piece Rate	Working Time
Entry into high-income destinations	0.22	0.21	0.11 (52%)	0.01 (5%)	0.09 (43%)
Entry into non-high-income destinations	-0.01	-0.12	-0.02 (22%)	0.00 (-1%)	-0.10 (79%)

Notes: The data on experience returns with regard to export entry is the average of reduced-form evidence in Tables D.11 and D.13 based on the matching estimator. The percentage in brackets refers to the contribution of each channel to the overall model-generated change.

high-income countries. Finally, entry into non-high-income destinations is associated with negative returns in experience returns, as exporting to non-high-income destinations may reduce the increment in human capital per time, and higher revenues per labor following export entry also increase the opportunity costs of investing in human capital.[27]

Our quantitative model finds a small role of changes in worker-firm rent sharing (measured by piece rates) in explaining the wage profiles, in line with Arellano-Bover and Saltiel (2021) who show that in Brazil, returns to experience are not much different between all workers and the sample of displaced workers who lose bargaining positions. This quantitative finding is mainly driven by a high value of workers' wage bargaining power ($\beta = 0.6$): as workers already gain good bargaining positions when hired, there is relatively small room for workers' wages to grow through wage negotiations when workers are poached. In Section F.4.1, we show that with a low value of workers' wage bargaining power, the role played by changes in worker-firm rent sharing in determining wage profiles becomes much more important.

F.4 Robustness Checks of Quantitative Model

F.4.1 Alternative parameterization

We provide several robustness checks on how the key parameters regarding human capital formation and worker-firm rent sharing affect the gains in human capital from trade, as summarized by Table F.4.

In the first exercise, we change the depreciation rate of human capital from $\delta_h = 0.02$ (baseline calibration) to $\delta_h = 0.01$, according to evidence on the life-cycle record performance (Lagakos et al., 2018). A smaller depreciation rate of human capital increases workers' incentives to invest in human capital, thus leading to a higher human capital level in autarky. Therefore, compared with baseline results, trade-induced human capital investment faces stronger diminishing returns and results in smaller gains in human capital from trade.

In the second exercise, we alter the on-the-job search intensity from $\eta = 0.12$ in the baseline to $\eta = 0.4$, which is the level in the United States (Faberman et al., 2017). A larger on-the-job search intensity speeds up workers' reallocation toward firms that are more productive and offer better learning. This reallocation force also interacts with trade openness, because with export revenues, productive firms post more vacancies and make up a larger share of the offer distribution. Thus, we

[27] It is worth noting that the changes in experience returns after entry into non-high-income destinations are estimated with much noise in the data. Our model-generated changes in experience returns after entry into non-high-income destinations are similar in magnitude to the reduced-form evidence based on the event study in Figure D.5.

Table F.4: Robustness Checks

	Gains from Trade		Decomposing ΔExperience Returns (after entry into high-income dests)		
	Real Income	Human Capital	Human Capital	Piece Rate	Working Time
(1) Baseline	7.78%	3.98%	52%	5%	43%
Alternative parameterization:					
(2) HC depreciation rate $\delta_h = 0.01$	7.00%	2.59%	37%	6%	57%
(3) On-job search intensity $\eta = 0.4$	8.08%	4.07%	39%	18%	43%
(4) Workers' bargaining power $\beta = 0$	6.97%	2.13%	28%	44%	28%
Alternative assumptions:					
(5) Model with LBD	12.41%	6.90%	94%	6%	0%

Notes: "LBD" is short for "learning-by-doing." The last three columns compute the contribution of each factor to changes in returns to 20 years of experience (after entry to high-income destinations), in the same way as in Table F.3.

find that allowing for a larger on-the-job search intensity slightly increases the gains in real income and human capital from trade.

In the third exercise, we change workers' bargaining power from $\beta = 0.6$ in the baseline to $\beta = 0$, an extreme scenario considered in Fajgelbaum (2020). Compared with baseline results, assuming $\beta = 0$ implies smaller starting wages for workers, thus indicating a larger role of wage renegotiations in explaining wage profiles (hence a smaller role for human capital). As a result, the gains in human capital from trade become smaller.

For each exercise, the last three columns in Table F.4 report the decomposition of changes in within-job experience returns (after entry into high-income destinations) into different factors. We find the contribution of wage negotiations is quite sensitive to workers' bargaining power β. In our baseline model, with a high calibrated value of workers' bargaining power ($\beta = 0.6$), workers already have good bargaining positions when hired, and there is small room for workers' wages to grow through wage negotiations. However, with a low value of workers' bargaining power ($\beta = 0$), there is much larger room for wage negotiations, as workers start with low bargaining positions and use poaching firms as the outside option to gain better bargaining positions.[28] We find that changing on-the-job search intensity (poaching rate) also considerably affects the contribution of wage negotiations, as workers can trigger negotiations more often when they are poached more.

F.4.2 Model with learning-by-doing

In our model, all human capital growth requires endogenous human capital investment à la Ben-Porath, whereas human capital may also be acquired through learning-by-doing (LBD). Section E.7 presents the model extension to consider that all human capital comes from LBD, and that the human capital processes can potentially vary across firms and ages (e.g., Bagger et al., 2014;

[28]As shown in Section III.B, if the joint surplus of the job at poaching firms is higher than workers' current value but lower than the joint surplus of the current job, workers' value will increase to the joint surplus of the job at poachers, even though they could not get a share of the difference in the joint surplus between poachers and the current firm because of $\beta = 0$. Because workers start with low bargaining positions, the difference between workers' value and the joint surplus of the job at the current firm is large.

Table F.5: Gains in Human Capital from Trade with Alternative Labor Market Frictions

	Gains in Human Capital from Trade
(1) Baseline	3.98%
(2) Job finding rate $\lambda_U = 1$	3.83%
(3) Job separation rate $\kappa = 1$	2.08%
(4) Both $\lambda_U = 1$ & $\kappa = 1$	1.97%

Gregory, 2021). We recalibrate the parameters of this extended model to match all the targeted moments in Table F.1.

The last row in Table F.4 reports that the gains in human capital from trade are 6.90% in the LBD model, compared with 3.98% in the baseline model. Although it is difficult to quantitatively determine the portions of human capital coming from investment and LBD, we view these two results as informative of upper and lower bounds of the gains in human capital from trade. With no time costs of human capital accumulation, the LBD model attributes most of changes in wage profiles (due to export entry) to human capital growth and thus provides an upper bound for the gains in human capital from trade. On the other hand, in our model, human capital formation relies on endogenous choices of time spent on learning. As young workers spend more time on learning than old workers, work time is upward sloping over the life cycle. This upward trend in work time over the life cycle would naturally explain a portion of experience-wage profiles. Thus, compared with the LBD model, our baseline model attributes a smaller portion of lifetime wage profiles to human capital growth, thus leading to a more conservative assessment about the role of human capital in shaping the gains from trade.

F.5 Role of Labor Market Frictions

Besides human capital formation, another major departure of our model from the canonical heterogeneous firm model (Melitz, 2003) is the addition of labor market frictions, which is key to modeling worker-firm negotiations. To understand how labor market frictions affect the gains in human capital from trade, we perform three additional quantitative exercises. In the first exercise, we set job finding rate $\lambda_U = 1$, which ensures full employment in the model economy. In the second exercise, we set job destruction rate $\kappa = 1$, under which assumption firms behave like hiring in a spot market in each period, resembling the typical assumption in the Melitz model (Melitz, 2003). In the final exercise, we set both job finding rate $\lambda_U = 1$ and job destruction rate $\kappa = 1$. In these three exercises, we hold all other parameter values at their baseline values.

In Table F.5 shows that, in the exercise with full employment (job finding rate $\lambda_U = 1$), the gains in human capital from trade decline compared to the baseline results. This is mainly due to the fact that, in the baseline model, trade openness encourages job vacancies and reduces the duration of unemployment, which also facilitates human capital formation (unemployed workers do not accumulate human capital), and this channel is absent from the model with full employment. With job separation rate $\kappa = 1$, the gains in human capital from trade also decline compared with the baseline results. Here, the lower gains are partly driven by the reduced concentration of employment in more productive firms due to the absence of job-to-job transitions,[29] which disfavors human capital formation as more productive firms also provide more learning opportunities. Finally, if we set both job finding rate $\lambda_U = 1$ and job destruction rate $\kappa = 1$, due to the combined effects, the decline in the gains in human capital becomes even larger compared with separately setting $\lambda_U = 1$ or $\kappa = 1$.

[29]The Pareto shape parameter of the firm employment distribution increases from 1.21 in the baseline calibration to 1.53 when we set the job destruction rate to unity, indicating the reduced concentration of employment in more productive firms.

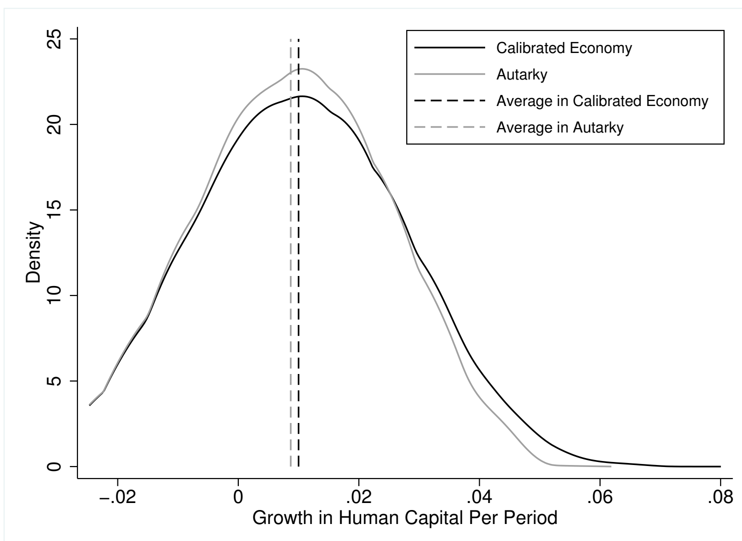
G Additional Tables and Graphs

Table G.1: Identification of Parameters γ_1 and γ_2

	Slope of Experience Returns on Firm Size	ΔExperience Returns (after entry into high-income dests)
Elasticity w.r.t γ_1	1.20	0.06
Elasticity w.r.t γ_2	0.49	4.81

Notes: In this table, we report the elasticity of model moments to parameter γ_1 (which governs how human capital increment varies with firm productivity) or γ_2 (which governs how human capital increment varies with destination markets' knowledge) under the baseline calibration, holding all other parameter values at their baseline values.

Figure G.1: Distribution of Human Capital Growth



Notes: The figure plots the distribution of per-period human capital growth across workers in the calibrated and autarkic economies, respectively, with the auxiliary vertical lines representing respective averages.

Appendix References

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