Learning by Exporting and Wage Profiles: New Evidence from Brazil

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Abstract

Export activity shapes workers' experience-wage profiles. Using detailed Brazilian manufacturing employer-employee and customs data, we document that workers' experience-wage profiles are steeper at exporters than at non-exporters. Aside from self-selection of more capable firms into exporting, we show that workers' experience-wage profiles are steeper when firms export to high-income destinations. We then develop and quantify a model with export market entry, wage renegotiations, and human capital accumulation to interpret the data and perform counterfactual experiments. We find that human capital growth can explain roughly 40% of differences in wage profiles between exporters and non-exporters as well as the gains in experience returns after entry into high-income destinations. We also show that increased human capital per worker can account for one-half of the overall gains in real income from trade openness. In slowing human capital accumulation, trade liberalization can induce welfare losses if the trade partners are low-income destinations.

Keywords: Export Activity; Wage Profiles; Human Capital Accumulation
JEL Codes: E24, F12, F14, F16, J24, J64

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1 Introduction

It is well-known that exporters are more productive than non-exporters. This differential is partly driven by self-selection of more capable firms into export activity (e.g., Clerides et al. 1998). There can also be productivity improvements after exporting. For example, Atkin et al. (2017) find that exporting improves firms' technical efficiency in a randomized experiment, and De Loecker (2007) shows that firms' productivity gains may increase when firms export to high-income countries.[1] These existing studies mostly focus on firm-level outcomes, whereas exporting may impact workers and firms jointly. It is well-documented that workers earn higher wages at exporters than at non-exporters (Bernard and Jensen 1995). However, despite much attention to firm-level differences in lifecycle wage growth in recent studies (Herkenhoff et al. 2018, Jarosch et al. 2018, Gregory 2019),[2] little is known about how firms' export activity shapes workers' lifecycle wage dynamics.

We study empirically the relationship between a firm's export activity and its workers' wage profiles. We rely on Brazilian linked employer-employee data and customs records between 1994–2010, assembling a long-run panel with detailed job information. To construct experience-wage profiles, we measure a worker's potential experience in the labor market as years elapsed after schooling and then estimate how one extra year of experience within a job (firm-worker match) affects wage growth for workers in different lifecycle stages measured by potential experience. In principle, one more year of experience and changes in aggregate time effects can both lead to wage changes. To resolve this well-known collinearity problem (Deaton 1997), we apply the broadly used Heckman–Lochner–Taber (HLT) approach (e.g., Heckman et al. 1998, Huggett et al. 2011, Bowlus and Robinson 2012, Lagakos et al. 2018). The centerpiece of this approach is to assume no experience returns in the end of the working life,[3] and hence old workers' wage growth allows us to isolate time effects.

We document three facts. First, for a person staying in a job for 20 years from the beginning of her career, her wage growth is 85% at non-exporters and 104% at exporters, indicating a sizeable difference of 19 percentage points in lifecycle wage growth between exporters and non-exporters. Second, firm productivity proxies and firm fixed effects explain

[1]For more evidence on the comparison of productivity levels between exporters and non-exporters, see also Bernard and Jensen (1999), Aw et al. (2000), Van Biesebroeck (2005), Lileeva and Trefler (2010), Aw et al. (2011), and De Loecker (2013), among others.

[2]Herkenhoff et al. (2018) and Jarosch et al. (2018) study the effects of exposure to coworkers, and Gregory (2019) explores the impact of firm-specific human capital accumulation.

[3]A large number of theories of lifecycle wage growth find that there are little returns to experience in the final working years (Rubinstein and Weiss 2006).

most of the differences in experience-wage profiles between exporters and non-exporters, hinting that exporters essentially provide higher returns to experience. Third, after controlling for productivity proxies, labor composition, and firm fixed effects, returns to experience are still higher when firms export to high-income destinations. We find that the increase in returns to experience materializes immediately following firms' entry into high-income destinations, and this result is robust when we apply the propensity-matching approach to lessen the endogeneity concern of export decisions.

We show our empirical results do not rely on the HLT approach. For workers who have been observed since a young age, instead of using age and schooling to construct potential experience, we construct experience based on their observed employment history. Because of possible breaks in observed employment records (due to reasons such as unemployment), which resolve the collinearity between experience and time, we thus do not need to impose the HLT assumption in estimation. Using this sample, we still find that previous experience at exporters (especially those who export to high-income destinations) is more valuable than experience at non-exporters, and that these experience effects persist after switching firms. The estimated experience effects are of similar magnitude to our previous findings. We also show similar results for a sample of displaced workers due to sudden closure of large firms, as these workers' returns to previous experience are more likely to be shaped by learning than seniority (Jacobson et al. 1993, Dustmann and Meghir 2005).

The impact of export activity on wage profiles can reflect human capital accumulation as well as changes in firm-worker rent sharing, as suggested by a large literature quantitatively studying the earnings dynamics (e.g., Bunzel et al. 1999, Rubinstein and Weiss 2006, Barlevy 2008, Yamaguchi 2010, Burdett et al. 2011, Bowlus and Liu 2013, Bagger et al. 2014, Gregory 2019). The second contribution of this paper is to develop and quantify a model with firms' export market entry, wage renegotiations, and human capital accumulation to interpret the data and conduct experiments.

Our model builds on Cahuc et al. (2006), in which firms post vacancies and meet workers by random search, and wages can be renegotiated when workers are poached by other firms. Guided by our evidence, we embed two novel features into the model. First, we consider that the increment in human capital per time spent increases with firm productivity and the sales-weighted average knowledge stock in firms' markets.[4] Thus, staying in highly productive firms (which tend to select into exporting) and being exposed to destinations

[4]Modelling the dependence of learning returns on firm productivity is also used by Monge-Naranjo (2016) and Engbom (2020), but they do not consider that human capital gains depend on firms' product markets.

with affluent knowledge can produce faster human capital growth. Second, we consider destinations to be heterogeneous in their levels of knowledge stock, and therefore different combinations of destinations imply vastly different learning opportunities for workers.[5]

In the model, workers' within-job wage profiles reflect human capital growth, changes in time allocated to human capital investment, and wage renegotiations. To understand their relative contributions, we calibrate our model to the Brazilian manufacturing sector and target the relevant moments to discipline the strength of wage renegotiations and human capital investment. In the calibrated model, human capital growth can explain 70% of the overall within-job wage profiles. However, because of diminishing returns to human capital investment, human capital growth can only explain 40% of differences in wage profiles between exporters and non-exporters as well as the gains in experience returns after entry into high-income destinations. Our calibrated model is also capable to match the observed decline in experience returns after entry into non-high-income destinations.

We then use our calibrated model to understand the quantitative effects of trade openness. In the first counterfactual exercise, we find that the gain in real income from autarky to the calibrated economy is 9.50%. A large contributor is faster human capital growth with exposure to high-income destinations—workers enjoy a 4.86% increase in average efficiency labor due to trade openness. In the second exercise, we lower trade costs from Brazil to specific export destinations. The gains in real income depend on destinations' knowledge stock and are not necessarily positive. Lowering trade costs to high-income destinations by 10% would increase Brazil's real income by 2.70%, largely due to a 2.12% increase in workers' average human capital. Surprisingly, lowering trade costs to non-high-income destinations by 10% would reduce Brazil's real income by 0.21%, mainly driven by a 0.73% decline in workers' average human capital. In the third exercise, we find that higher knowledge stocks from trade partners would increase Brazil's real income through changes in workers' human capital. Finally, we show that assuming learning-by-doing (exogenous human capital processes) instead of endogenous human capital investment would amplify the gains in human capital from trade, because with no changes in time allocated to human capital accumulation, costless human capital growth plays a larger role in explaining the wage profiles.

This paper relates to several strands of the literature. We directly contribute to the

[5] This setting is also in contrast with papers that incorporate trade into similar models with labor hiring constraints (e.g., Fajgelbaum 2019, Dix-Carneiro et al. 2019), which typically model an aggregated rest of world. Modelling multiple destinations implies a hard permutation problem for deciding the set of export destinations from all feasible combinations, as firms' selling decisions are interdependent across markets in such models, and is thus computationally demanding.

literature on learning by exporting. Recent papers show that through acquiring new knowledge from exporting, firms can improve their technical efficiency (Aw et al. 2000, De Loecker 2013, Atkin et al. 2017) or understanding of export demand (Albornoz et al. 2012, Morales et al. 2019). Few studies explore how workers may also acquire knowledge from exporting. Exceptions are Mion and Opromolla (2014) and Muendler and Rauch (2018) who find that employees' previous experience at exporters is valuable for their new employers' choices of export markets. In contrast with these studies, we look into how export activity affects workers' lifecycle wage growth within the firm. Our results indicate that exporting may enhance workers' human capital, especially with exposure to advanced export destinations.

We also make contact with research on lifecycle wage growth. The literature has proposed many factors affecting lifecycle wage growth, such as job search (Bagger et al. 2014), human capital accumulation (Manuelli and Seshadri 2014), industry composition (Dix-Carneiro 2014), and match quality (Menzio et al. 2016).[6] To our knowledge, our study is the first to explore the role of a firm's export activity in shaping its workers' wage profiles. Moreover, much empirical work finds wage differences between exporters and non-exporters but abstracts from experience returns (e.g., Bernard and Jensen 1995).[7] We show that the exporter wage premium increases with workers' experience. Finally, recent studies highlight the importance of lifecycle wage growth in accounting for cross-country income differences (Islam et al. 2018, Lagakos et al. 2018). Our results imply that incentivizing exporting to high-income may reduce the cross-country income gap.

Our paper is also related to the literature that uses quantitative trade models with labor market search frictions (e.g., Helpman and Itskhoki 2010, Cosar et al. 2016, Dix-Carneiro et al. 2019, Fajgelbaum 2019). The most related paper is Fajgelbaum (2019) who also builds on the model of labor search and wage renegotiations in Cahuc et al. (2006). Fajgelbaum (2019) focuses on the interaction between labor market frictions and firm export decisions, and his model abstracts from human capital and workers' lifecycle. In contrast, our analysis focuses on the impact of export activity on workers' wage dynamics and thus embeds a rich modelling of workers' human capital accumulation and lifecycle choices.

Finally, we connect with a large literature on international knowledge diffusion. Many studies use macro aggregates (e.g., output, TFP, and R&D) to empirically study international

[6] Islam et al. (2018) show how a lot of factors, such as sectors, occupations, and Internet penetration, determine returns to experience.

[7] The literature finds that the exporter wage premium is composed of differences in labor composition and wage premia for workers with identical characteristics, including Schank et al. (2007), Frias et al. (2009), and Krishna et al. (2014). These existing studies abstract from workers' experience returns.

knowledge diffusion (e.g., Coe and Helpman 1995, Eaton and Kortum 1999), as reviewed by Keller (2021), highlighting that good economic performance of outward-oriented economies is particularly due to knowledge spillovers from foreign countries. Recent theoretical papers also explore the relation between trade-induced knowledge diffusion and firm productivity growth (e.g., Alvarez et al. 2013, Perla et al. 2015, Sampson 2016, Buera and Oberfield 2020).[8] This literature links trade with knowledge diffusion, whereas our results highlight that workers' human capital accumulation may also reflect trade-induced knowledge flows.

This paper is organized as follows. Section 2 describes our empirical findings on export activity and experience-wage profiles, and highlights the interaction between wage profiles and destination markets. To understand the facts and perform the quantitative analysis, Section 3 develops a small-country model with export activity, wage renegotiations, and human capital accumulation. Section 4 calibrates the model to match the data moments, and Section 5 performs several counterfactual exercises to understand the role of trade openness in affecting human capital and real income. Section 6 concludes.

2 Experience-Wage Profiles and Exporting

In this section, we document a set of stylized facts on how export activity affects experience-wage profiles in Brazil. We show that experience-wage profiles are steeper at exporters than non-exporters. We then show that higher experience-wage profiles at exporters reflect both selection of more capable firms into exporting and the effects of entering more advanced export destinations.

2.1 Data

Brazil constitutes a good case study for several reasons. First, Brazil has great data availability, as described below. Second, Brazilian exporters sell to a wide range of destinations, allowing the exploration of how export destinations shape wage profiles. For example, in 2010, Brazil's exports were not only directed to high-income countries (10% of total exports to the U.S., 25% to Europe, and 4% to Japan), but also to middle- and low-income countries (23% to Latin America, 15% to China, and 10% to Middle East and Africa). Appendix A.1 describes details of the Brazilian economy and exports during our sample period.

We rely on the RAIS database between 1994–2010. It provides a complete depiction of

[8]See Lind and Ramondo (2019) for a review.

workers employed in the Brazilian formal sector, because firms are mandated (by law) to annually provide workers' information to RAIS (Menezes-Filho et al. 2008).[9] Each datapoint represents a worker-firm-year observation, containing worker ID, firm ID, and workers' information on schooling, age, hourly wage, occupation, and other demographic information. One limitation of the data is the absence of information about the informal sector. Appendix A.2 discusses the characteristics of the Brazilian informal sector and shows that including informal workers in the sample may strengthen our empirical results.

We restrict our empirical analysis to manufacturing firms, which are tradable and extensively studied. In addition, we focus on full-time male workers aged between 18–65 and employed at firms with at least 10 employees.[10] If a worker has multiple records in a year, we select the record with the highest hourly wage (Dix-Carneiro 2014). Under these restrictions, we obtain a sample of 72 million observations in the period 1994–2010, including 17 million unique worker IDs and 229 thousand unique firm IDs. We also provide details on the industry and occupation classification of the database in Appendix B.

We use firm IDs to merge the RAIS data with Brazilian customs declarations for merchandise exports collected at SECEX for the years 1994–2010. We define a firm as an exporter in a given year if the firm has export transactions in that year. The SECEX data provides which destinations and 8-digit products each firm export in each year, whereas for 1997–2000, the data also provides information on detailed export quantity and value (U.S.$).

Table 1 describes characterizations of the RAIS database, based on worker-firm-year observations. On average, relative to 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). Moreover, exporters are much larger in terms of employment than non-exporters. These pieces of evidence are consistent with the exporter premium typically found in the literature (e.g., Bernard et al. 2003, Verhoogen 2008). Finally, 49% of worker-firm-year observations are at exporters, and thus export activity is nontrivial in our sample.

[9]The ministry of labor estimates that above 90% of formally employed workers in Brazil were covered by RAIS throughout the 1990s. The data collection is typically concluded by March following the year of observation (Menezes-Filho et al. 2008). 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.

[10]The restrictions on full-time male workers follow Lagakos et al. (2018), due to large changes in female labor participation rates. According to the World Bank's estimates for those aged 15+ in Brazil, female labor force participation rate increased from 45% in 1994 to 54% in 2010, whereas male labor force participation rate changed from 81% to 77% in the meantime. The restriction on firm size aims to avoid self-employment. The results are quantitatively similar if we restrict the employment size to be at least 5.

Table 1: Sample Statistics

Observations (72 million)	Non-exporter		Exporter	
	Mean	S.D.	Mean	S.D.
workers' characteristics:				
age	31.97	9.72	32.78	9.39
schooling	8.23	3.46	9.06	3.77
log(hourly wage), Brazilian Real$	0.67	0.77	1.20	0.96
cognitive occupations (1 if yes)	0.20	0.40	0.25	0.43
share of workers in the sample	0.51	–	0.49	–
firms' characteristics:				
log(employment)	4.51	1.56	7.05	1.71
log(exports per worker), U.S.$	–	–	8.09	2.31

Note: 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. The export value data is only available in 1997–2000, and hence log(exports per worker) is based on these four years.

In Appendix B.1, we use the raw data to present experience-wage profiles in the cross section, showing that workers at exporters have steeper wage profiles than workers at non-exporters.[11] As there are many identification problems with this first-pass attempt, we proceed to formally estimate experience-wage profiles.

2.2 Aggregate Experience-Wage Profiles by Export Status

Method. We consider a job as a firm-worker match and estimate experience-wage profiles using workers' within-job wage growth, following Bagger et al. (2014). In comparison with using wage levels to estimate experience returns (Islam et al. 2018, Lagakos et al. 2018), this approach takes advantage of the panel structure of our employer-employee data, controlling for individual, firm, and match-specific fixed effects that affect wage levels and avoiding the "incidental parameters" issue of estimating too many fixed effects (Arellano and Hahn 2007). Another strength of focusing on within-job wage growth is that it avoids potential wage changes related to job separations. We estimate the following regression:

$$\Delta \log(w_{it}) = \sum_{x \in X} \phi_s^x D_{it}^x + (\gamma_{st} - \gamma_{st-1}) + \epsilon_{it}, \tag{1}$$

[11]We also find similar results as in the literature (Islam et al. 2018, Lagakos et al. 2018): more-educated workers, workers in bigger firms, and workers in more sophisticated occupations have steeper wage profiles.

where i and t represent individuals and years respectively. The subscript s is the level of aggregation for estimating experience returns (e.g., exporters and non-exporters), which will be specified in later implementation. $\Delta \log(w_{it})$ denotes within-job wage growth, which is log hourly wage growth from $t-1$ to t for individual i within the same firm.[12]

As we cannot observe all workers' full employment history, we follow Lagakos et al. (2018) to construct a measure of potential experience in the labor market as the minimum of age minus 18 or age minus 6 and schooling, min{age-18,age-6-schooling}. D_{it}^x is a dummy variable that takes the value 1 if a worker's current potential experience is in experience bin $x \in X = \{1\text{–}5, 6\text{–}10, ...\}$, where X is the set of 5-year experience bins. The parameter ϕ_s^x measures returns to one extra year of experience for workers in experience bin x, and thus we allow experience returns to nonparametrically differ across stages of the lifecycle (measured by experience bin x), because experience returns change as workers grow old.[13] γ_{st} represents time effects on wage levels at time t (e.g., TFP, price levels).

Estimating equation (1) faces the well-known collinearity problem regarding experience, individual effects, and time effects in the labor literature (Deaton 1997). This is easily seen as $\sum_x D_{it}^x = 1$ is perfectly correlated with the constant $(\gamma_{st} - \gamma_{st-1})$ for each aggregation level s and time t. Intuitively, entering a new year amounts to one more year of experience according to construction of potential experience, and wage growth over time can be induced by experience or better aggregate economic conditions (e.g., TFP growth). To disentangle returns to experience from aggregate trends, we adopt the HLT method used broadly in the literature (e.g., Huggett et al. 2011, Bowlus and Robinson 2012, Lagakos et al. 2018).[14] This approach introduces a restriction on experience returns, drawing on the basic prediction of a large number of theories of lifecycle wage growth that there are little experience returns in the final working years, and hence workers' wage growth in the final working years reflects time effects.[15] Implementing the HLT approach requires assumptions on two parameters: the number of years with no experience returns, and the depreciation rate. Following Lagakos et al. (2018), we consider 10 years at the end of the working life (31–40 years of experience) with no experience returns and a 0% depreciation rate, and these two parameters imply the restriction $\phi_s^{31-35} + \phi_s^{36-40} = 0$. Appendix C.1 provides more details on the approach.

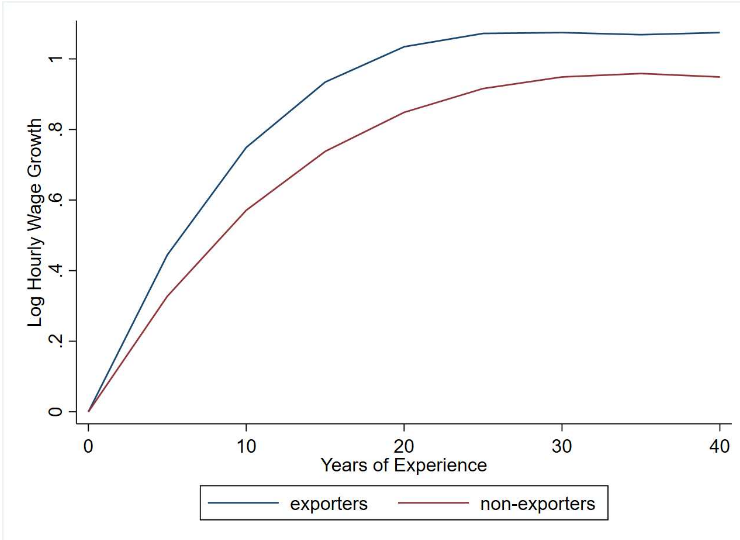
[12] As the time effects $\gamma_{st} - \gamma_{st-1}$ depend on the aggregation level s (e.g., exporters and non-exporters), we also require the corresponding firm status to remain constant from $t-1$ to t.

[13] Another common way to model experience returns is to assume a quadratic functional form (e.g., De La Roca and Puga 2017).

[14] See Lagakos et al. (2018) for a detailed description of the method.

[15] See Rubinstein and Weiss (2006) for a review of theories on lifecycle wage growth.

Figure 1: Log Hourly Wage Increase by Exporters and Non-exporters



Note: This figure presents the (employment-weighted) within-industry 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 10 years with no experience returns.

Estimation Results. We apply equation (1) to estimate experience-wage profiles using our sample. As returns to experience may differ across industries (Dix-Carneiro 2014), we always control for industry effects when comparing wage profiles between exporters and non-exporters.[16] Figure 1 presents the estimated experience-wage profiles at exporters and non-exporters. For a hypothetical person staying in a job for 20 years from the beginning of their career, her wage growth is 19 percentage points higher at exporters than at non-exporters, and the difference slightly declines to 14 percentage points after 40 years of experience.

In Appendix Figure E.1, we show that the differences in wage profiles between exporters and non-exporters are quantitatively very similar if we assume the final 5 years with no experience returns. An alternative value of depreciation shifts exporters' and non-exporters' wage profiles by the same amount and thus does not affect relative differences in wage profiles between exporters and non-exporters. Because depreciation rates can matter for the aggregate amount of human capital, we will calibrate and discuss the depreciation of human capital in the quantitative analysis.

[16]Specially, we estimate equation (1) separately for Brazilian workers within exporters and non-exporters, for each 3-digit industry. We then apply identical weights (total industry-level employment) to construct profiles for exporters and non-exporters. Consistently, we always control industry fixed effects in our firm-level regressions below.

2.3 Firm-level Wage Profiles and Export Destinations

To understand what drives differences in experience returns between exporters and non-exporters, we modify equation (1) to estimate firm-year-level returns to experience,

$$\Delta \log(w_{it}) = \sum_{x \in X} \phi^x_{\omega t} D^x_{it} + (\gamma_{\omega t} - \gamma_{\omega t-1}) + \epsilon_{it}, \tag{2}$$

where ω refers to a firm. The returns to experience $\phi^x_{\omega t}$ are now firm-specific and also time-variant to allow exploration of changes in firms' export status, as described below. This equation involves a large number of firm-specific parameters and usually requires grouping firms into several groups for estimation (Bonhomme et al. 2018). To exploit the firm-level information, instead of directly estimating equation (2), we make use of the same assumption of the HLT method that there are no experience returns for workers in the last 10 years of the working life, $\phi^{31-35}_{\omega t} + \phi^{36-40}_{\omega t} = 0$. Based on this assumption, the wage growth of the last two experience bins reflects the firm-specific wage trend $(\gamma_{\omega t} - \gamma_{\omega t-1})$. Hence, we can construct an estimate for annual returns to experience in experience bin x by

$$\hat{\phi}^x_{\omega t} = \frac{\sum_{i\in\omega} D^x_{it} \Delta \log(w_{it})}{\sum_{i\in\omega} D^x_{it}} - \frac{1}{2}\left(\frac{\sum_{i\in\omega} D^{31-35}_{it} \Delta \log(w_{it})}{\sum_{i\in\omega} D^{31-35}_{it}} + \frac{\sum_{i\in\omega} D^{36-40}_{it} \Delta \log(w_{it})}{\sum_{i\in\omega} D^{36-40}_{it}} \right). \tag{3}$$

$\frac{\sum_{i\in\omega} D^x_{it} \Delta \log(w_{it})}{\sum_{i\in\omega} D^x_{it}}$ represents the average individual-level log wage growth between $t-1$ and t, for workers at firm ω in both periods and in experience bin $x \in X = \{1–5,...,36–40\}$. By equation (3), we control for time-varying conditions (e.g., TFP growth, demand shocks) that alter wages for all workers within the firm. For instance, if the firm raises all workers' wage by the same proportion due to increased revenue after exporting, this effect will not show up in equation (3). However, if the wage growth is relatively higher for young workers than old workers, this relative difference will be interpreted as returns to experience.[17]

In Table 2, we regress firm-year-level returns to 20 years of experience on firm characteristics. The dependent variable is $5 \times \sum_{x\in\{1-5,...,16-20\}} \phi^x_{\omega,t}$, measuring the hypothetical lifecycle wage growth of a worker staying at firm ω for 20 years from the beginning of their career, with returns to experience fixed at time t. We choose to report returns to 20 years of experience, because many firms do not have workers in all experience bins and workers have

[17] Besides estimating firm-level wage profiles, the main difference from the method in Section 2.2 is that the previous method estimates average experience returns over time and only requires average experience returns in the last ten years to be zero. If we also estimate time-variant experience returns ϕ^x_{st} in Section 2.2 and restrict $\phi^{31-35}_{st} + \phi^{36-40}_{st} = 0$ at each time t, we can then obtain ϕ^x_{st} similarly as in equation (3).

Table 2: Wage Profiles and Firm Characteristics

	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***	0.018	-0.016	-0.050	-0.082	-0.050
	(0.013)	(0.026)	(0.035)	(0.073)	(0.127)	(0.125)
Exporter × ratio of # high-income to # total dests			0.134***	0.237**		
			(0.052)	(0.110)		
Exporter × share of exports to high-income dests					0.180*	
					(0.104)	
Exporter × log(avg GDPPC of dests)						0.127**
						(0.062)
Exporter × log(# total dests)			-0.010	0.038	0.026	0.026
			(0.020)	(0.053)	(0.060)	(0.060)
Exporter × log(avg exports per employee)					0.010	0.008
					(0.030)	(0.022)
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	344,785	344,785	344,785	77,888	77,888	77,888
R-squared	0.007	0.318	0.318	0.488	0.488	0.488

Note: This table presents estimates from regressions of firm-year-level returns to 20 years of experience on firm characteristics. The baseline group is non-exporters. The controls are the shares of high-school and cognitive workers in the firm's workforce as well as firm size. Robust standard errors are in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

little returns to experience after 20 years of experience (Figure 1).

In Column (1), the independent variables are an exporter dummy (1 if a firm exports) and a set of industry and year fixed effects. The baseline group is non-exporters. We find that after 20 years of experience, workers' wage increase is 27 percentage points higher at exporters than at non-exporters, which is comparable in magnitude to the difference found earlier (Figure 1)—19 percentage points after 20 years of experience.[18]

In Column (2), we control for the shares of high-school and cognitive workers in the firm's workforce, as labor composition can affect wage profiles (Islam et al. 2018). We further control for firm employment size, which is associated with firm productivity (Hopenhayn 1992), and firm fixed effects, capturing time-invariant unobserved factors. Surprisingly,

[18]The employment-weighted difference in returns to 20 years of experience between exporters and non-exporters is 18 percentage points. This aligns with the result in Figure 1, which is estimated using worker-level information and naturally puts higher weight on wage profiles at firms with larger employment size.

after including these controls, the resulting exporters' premium in returns to experience declines (relative to Column (1)) and nearly vanishes. We find that only controlling for labor composition explains 19% of the decline in the exporters' premium, whereas only controlling for firm employment explains 60% of the decline. These results suggest that higher returns to experience at exporters reflect selection of better firms into exporting.

We explore the dependence of wage profiles on export destinations in Columns (3)–(6). In Column (3), for each exporter in each year, we include the ratio of the number of high-income destinations to the total number of export destinations. We classify countries into high-income countries according to the World Bank classification in 2000.[19] We also control for the number of export destinations, as the scope of destinations may matter. We find that firms that export more to high-income destinations also experience steeper wage profiles. The coefficient suggests that other things being constant, a firm exporting solely to high-income countries has a 13-percentage-point higher returns to 20 years of experience than an exporter that does not sell any output to high-income countries.

In Columns (4)–(6), we exploit firm-level detailed data on export value for the 1997–2000 period. Column (4) replicates the regression of Column (3) for 1997–2000. We still find that exporting to high-income countries increases wage profiles in 1997–2000, though the coefficients become noisier due to a smaller sample size. In Column (5), we measure an exporter's exposure to high-income countries by the share of exports to high-income destinations in its total exports. We also control for export value per employee, as destination-specific effects may originate from increased revenue due to exporting. In line with previous results, larger shares of exports to high-income destinations significantly increase returns to experience. We also find that controlling for export value per employee has little effects on the coefficients. In Column (6), we measure a firm's destination-specific exposure by using export-weighted GDP per capita across export destinations.[20] We find that exporting to destinations with higher income significantly increases returns to experience.

In Appendix Table D.1, we replicate the results in Table 2 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 experi-

[19] In 2000, the World Bank classifies countries into high-income countries if their GNI per capita is higher than $9,265. To avoid that our results are affected by 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.

[20] To avoid that our results are driven by time trends of GDP per capita, we use each country's GDP per capita in 2000 to compute firms' export-weighted GDP per capita across export destinations in 1997–2000.

enced managers and coworkers (Mion and Opromolla 2014, Muendler and Rauch 2018).

In Appendix Table D.2, we divide industries into differentiated and non-differentiated industries.[21] We show that differentiated industries enjoy large and significant increases in returns to experience due to high-income destinations, even after controlling for export value, whereas 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.[22] Our main analysis focuses on manufacturing, whereas Brazil also exports agricultural and mining products (see Appendix A.1). Appendix Table D.2 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.

Before providing a quantitative analysis of possible causes of experience effects, we now show more supportive evidence that changes in returns to experience related to high-income destinations are caused by export activity.

2.4 Changes in Profiles around Entry to High-income Destinations

We first construct an event study to show that changes in returns to experience related to high-income destinations materialize immediately when firms start exporting. We perform the following regression:

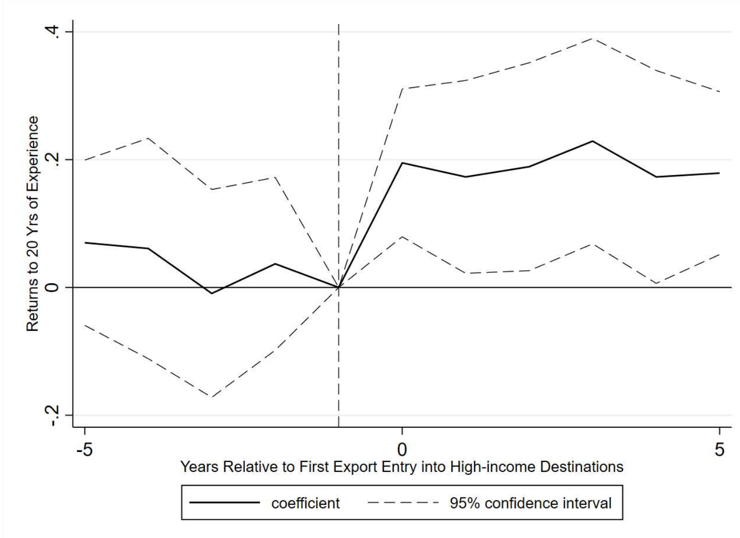
$$\begin{aligned} y_{\omega,t} = &\sum_{\tau=-4}^{\tau=-2} \beta_\tau 1\{high\_inc\}_{\omega,t^*+\tau} + \sum_{\tau=0}^{\tau=4} \beta_\tau 1\{high\_inc\}_{\omega,t^*+\tau} + \beta_{pre} \sum_{\tau\leq -5} 1\{high\_inc\}_{\omega,t^*+\tau} \\ &+ \beta_{post} \sum_{\tau\geq 5} 1\{high\_inc\}_{\omega,t^*+\tau}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

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 the shares of high-school and cognitive workers, firm size, and a dummy variable indicating whether the firm is exporting to a non-high-income destination.

[21] 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).

[22] For example, as Artopoulos et al. (2010) 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 to make their marketing practices more sophisticated" (p. 6).

Figure 2: Dynamics of Firms' First Entry Into High-income Destinations



Note: The figure shows the β_τ parameters from estimating equation (4). 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, the shares of high-school graduates and cognitive workers in the workforce, firm size, and a dummy variable indicating whether the firm is exporting to a non-high-income destination. To estimate the β_τ parameters after entry, we require that firms remain exporting to high-income destinations.

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 2 presents the results from estimating equation (4). 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. 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. Appendix Figure E.2 estimates the β_τ parameters for the firm's first export entry

Table 3: Returns to 20 Yrs of Experience for New Exporters to High-income Destinations

Post-exporting period	0	1	2	3
(a) Outcome: returns to experience				
Export entry	0.139*	0.177*	0.344***	0.249*
	(0.073)	(0.095)	(0.119)	(0.138)
Nr treated	4,164	2,191	1,693	1,477
Nr controls	158,734	118,285	93,056	75,150
(b) Outcome: growth in returns (relative to $\tau = -1$ period)				
Export entry	0.214**	0.251*	0.065	0.383**
	(0.110)	(0.141)	(0.187)	(0.193)

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—returns to 20 years of experience, the shares of high-school and cognitive workers, firm size, and export status to non-high-income destinations, as well as 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%.

into non-high-income destinations at time $t = t^*$ ($\tau = 0$). We find no statistically significant change in returns to experience after entry to non-high-income destinations.

To control for the self-selection process of exporting, we apply the propensity-score matching estimator as suggested by Heckman et al. (1997) (see Appendix C.2 for details on the approach).[23] We first estimate each firm's probability to start to export to high-income destinations based on a Probit model. We include a host of pre-exporting (previous year) firm characteristics, including returns to 20 years of experience, the shares of high-school and cognitive workers, firm size, and export status to non-high-income destinations, as well as industry and year fixed effects. The matching is based on the method of the nearest neighbor,[24] which selects a non-exporting firm which has a propensity score closest to that of the export entrant. We find that the first moments of the covariates are not different for the treated and the control units (balancing hypothesis, see Rosenbaum and Rubin (1984)).

Panel (a) of Table 3 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

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

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

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 2 and Figure 2.

In Appendix Table D.3, we find no significant differences in the shares of high-school and cognitive workers between new exporters and non-exporters in the period of export entry. This indicates that changes in labor composition may not explain increases in returns to experience because of export entry. The subsection below explores worker-level regressions to further confirm that our results are not driven by changes in labor composition after entry. Appendix Table D.4 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 almost vanishes. This suggests that large increases in returns to experience are associated with continuing exporting to high-income destinations, and there can exist some persistent effects after stopping exporting. Finally, Appendix Table D.5 replicates Table 3 for entry to non-high-income destinations, and we find no statistically significant changes in returns to experience after export entry.

2.5 Worker-level Results

In Appendix C.3, we construct a panel of young workers that enter RAIS under 25 years old (arguably the beginning of the career).[25] Using this restricted sample has several strengths. First, instead of constructing potential experience based on age and schooling, we can now construct these young people's experience using their observed employment history in RAIS. Second, because of possible breaks in employment history due to reasons such as unemployment (thus entering a new year does not necessarily imply one more year of experience), their observed experience does not have the collinearity problem with year effects. Thus, we no longer require the HLT approach in estimation.

We perform panel regression to estimate how workers' previous work experience affects their current wages, controlling for individual fixed effects and time effects. In comparison with previous subsections, here we do not restrict workers' wage growth to be within a job in order to understand how experience affects wages after switching firms. We have three findings. First, we find that if a new worker starts a job at exporters, she enjoys a 4.8% wage premium relative to a job at non-exporters. If she continues to work at exporters, she enjoys

[25] To extend the work history, we supplement our sample in 1994–2010 with RAIS and customs data in 1986–1993, for which we do not observe hourly wage but can construct workers' experience.

a 16.5% higher wage growth than working at non-exporters over 20 years of experience, in line with the results in Section 2.2. Second, we find that the experience effects persist after switching firms. According to the estimates, if a worker starts to work in a new firm after 20 years of experience in an exporter, she enjoys a 10.5% higher wage than previously working at non-exporters for 20 years. Finally, 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 15% higher wage growth than working at exporters that only export to non-high-income destinations. This result is of similar magnitude as our firm-level results in Table 2.

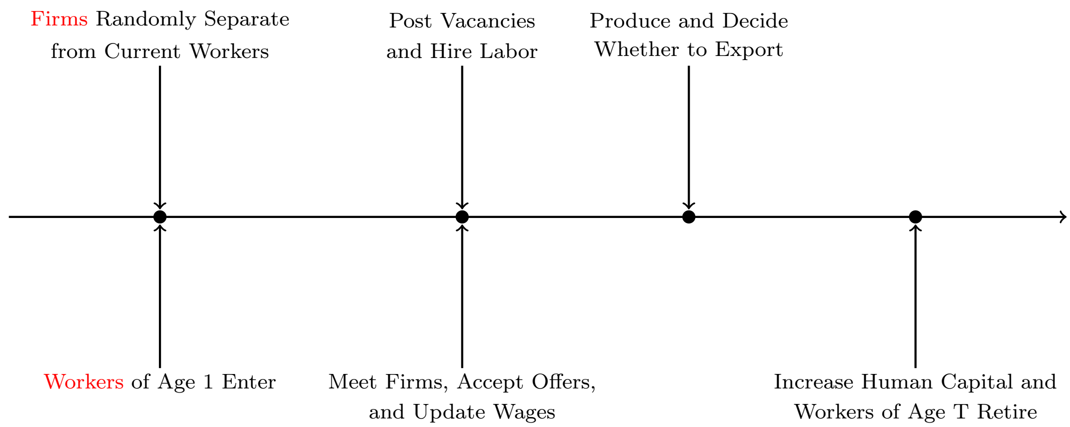
We further analyze a sample of displaced workers due to closure of large firms, because, after displacement, these workers' returns to previous experience are more likely to be shaped by learning than seniority, following the labor literature (Jacobson et al. 1993, Dustmann and Meghir 2005, Arellano-Bover and Saltiel 2021). We still find that previous experience at exporters is more valuable for their post-displacement earnings than experience at non-exporters. 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 15% higher post-displacement earnings than previously working at exporters that only export to non-high-income destinations. This finding is of similar magnitude to the results from the full sample of all young workers.

3 Model

To understand the factors behind the impact of export activity on wage profiles and its aggregate implications, we proceed to develop and quantity a model. As suggested by our evidence and a large literature on the earnings dynamics (e.g., Bunzel et al. 1999, Rubinstein and Weiss 2006, Barlevy 2008, Yamaguchi 2010, Burdett et al. 2011, Bowlus and Liu 2013, Bagger et al. 2014, Gregory 2019), we consider that wage profiles reflect human capital accumulation as well as changes in firm-worker rent sharing.

In the model, firms meet unemployed or employed workers by random search and decide whether to sell in foreign markets. Workers' within-job wage grows due to endogenous human capital accumulation and wage renegotiations. The increment in human capital per time spent depends on the knowledge stock of destination markets, and different destinations are heterogeneous in their knowledge stocks. We focus on a steady state in which aggregate variables are constant. The timing of events in each period is provided in Figure 3.

Figure 3: Timing of Events in Each Period



3.1 Workers, Labor Market Frictions, and Human Capital

There is a unit mass of overlapping generations of workers, with totally T cohorts. Workers participate in the labor market from age $t = 1, 2, .., T$. A fraction $1/T$ of workers of age T retire each period and are replaced by new entrants. Thus, the measure of workers in each age group is $1/T$. Workers have the linear utility for consumption of a nontradable final good, and they discount the future at rate ρ. The final good is aggregated over a set of differentiated varieties sourced from domestic or foreign origins, as we describe below.

Labor markets are subject to search frictions (Mortensen and Pissarides 1994, Pissarides 2000). At the beginning of each period, existing jobs are terminated at an exogenous rate κ. New entrants of age 1 begin as unemployed. Unemployed and employed people then learn of jobs randomly at rates λ_U and λ_E respectively. Let U be the total amount of unemployed people before job search happens, and η be the search efforts of employed people relative to unemployed people whose search efforts are normalized to 1. The meeting rates λ_U and λ_E are endogenously determined: $\lambda_U = \chi\left(\frac{V}{U+\eta(1-U)}\right)$ and $\lambda_E = \eta\lambda_U$, where $\frac{V}{U+\eta(1-U)}$ is the ratio of the amount of all firms' vacancies to workers' search efforts. The function $\chi(\cdot)$ governs the matching process.

In each period, workers can be employed or unemployed. If employed, workers differ in their employers and wages. As in Melitz (2003), we consider firms (employers) have different productivity levels, drawn from a distribution $\Phi(z)$. We use productivity z to index firms. We discuss the wage determination in Section 3.3. Workers also differ in their human capital. New entrants of age 1 are endowed with human capital normalized to $h_1 = 1$. Employed workers may accumulate human capital on the job. We assume that workers' human capital evolves as from age t to age $t+1$:

$$h_{t+1} = (1-\delta_h)h_t + \phi^E(z) i_t^{\alpha}. \tag{5}$$

Here δ_h is the depreciation rate. The efficiency units of time spent on human capital accumulation, i_t, are chosen to maximize the joint (firm + worker) value, as described below. $\phi^E(z)$ captures the increment in human capital per unit of time spent on building skills, and $0 < \alpha < 1$ captures the degree of diminishing marginal benefits with time. Guided by our empirical evidence, the key feature of our model is that given the same amount of time spent on accumulating human capital, the increment in human capital is firm-specific and depends on export destinations:

$$\phi^E(z) = \mu z^{\gamma_1} \left(\phi^O(z)\right)^{\gamma_2}. \tag{6}$$

We model the increment as a Cobb-Douglas function of intra-firm knowledge and knowledge outside the firm, similarly as in Monge-Naranjo (2016), with γ_1 and γ_2 representing the elasticities of the increment with regard to intra-firm knowledge and knowledge outside the firm, respectively. We use firm productivity z to proxy the stock of productive ideas within the firm. $\phi^O(z)$ summarizes the set of productive ideas that are outside in firms' markets and available to workers in the firm. Let $s_n(z)$ be the share of sales to destination n in the firm's total sales, and λ_n denote the stock of knowledge gleaned from selling to country n. Then, $\phi^O(z) = \sum_n s_n(z)\lambda_n$ is a weighted average of destinations' knowledge.

The intuition of this learning function is as follows. Workers can grasp knowledge from their colleagues, through the on-site training, or by learning-by-doing, and these opportunities are more available at firms with more advanced technology (e.g., Arrow 1962, Jovanovic and Lach 1989, Hopenhayn and Chari 1991). Directly modelling the dependence of learning returns on firm productivity captures that better firms provide more learning, and this model setup is also exploited in recent papers (e.g., Monge-Naranjo 2016, Engbom 2020). Learning can also happen through interactions with the external environment. For example, firms may adjust their product requirements for different destination markets (Verhoogen 2008, Manova and Zhang 2012), and managers can also get new ideas by learning from the local people they do business with or compete with (Buera and Oberfield 2020). Although the previous literature mostly focuses on firm productivity[26] and has not studied how export destinations affect workers' human capital accumulation, it is natural to conjecture that workers' human

[26] The idea that trade flows may affect firm productivity dates back to Grossman and Helpman (1991) and is reviewed by Keller (2004).

capital accumulation may also be affected by destination-specific product requirements or personal interactions with clients. Because the share of sales to each destination in a firm's total sales proxies the proportion of product lines or employees devoted to that destination, we thus weight the exposure to destinations' technology by these sales shares.

3.2 Firm Revenues and the Trade Environment

The production side shares the central features of Melitz (2003). There is a mass $\bar{M}$ of monopolistically competitive firms with heterogeneous productivity levels $z \sim \Phi(z)$. Without loss of generality, we normalize $\bar{M} = 1$. Each firm produces a unique differentiated variety using labor as the only input. Varieties are internationally traded and aggregated into a final good in each country with a constant elasticity of substitution σ across varieties.

We consider $n = 1, 2, ..., N$ destination markets. In particular, we index the home country as the first market $n = 1$, and all other markets refer to foreign economies.[27] The small-open-economy assumption means that aggregate variables in foreign countries are invariant to conditions at home. Because of monopolistic competition, the quantity demanded for a variety in market n is $y_n = p^{-\sigma} P_n^{\sigma} Y_n$, where P_n and Y_n are the aggregate price index and quantity of the final good in market n, respectively. The price of the variety is determined as $p = y_n^{-\frac{1}{\sigma}} P_n Y_n^{\frac{1}{\sigma}}$. For firms in the home country, selling to market n incurs iceberg costs τ_n, as well as fixed costs f_n in terms of final goods in the home market. We assume the iceberg and fixed costs of selling in the home market to be $\tau_1 = 1$ and $f_1 = 0$, respectively.

For a firm with productivity z, producing one unit of good requires $1/z$ efficiency labor. To hire workers, firms need to post vacancies, and posting v vacancies costs $\frac{c_v v^{1+\gamma_v}}{1+\gamma_v}$ units of final goods. In the quantitative analysis, we assume $\gamma_v > 0$. This assumption generates the exporter premium, because it is increasingly costly to hire new workers, and thus increased demand due to exporting leads to larger average revenues for existing workers. Let $v(z)$ be the optimal amount of vacancies for firm z, as detailed below. The total number of vacancies is $V = \bar{M} \int v(z) d\Phi(z)$. We define $F(z) = \int_{z_{\min}}^{z} v(z') d\Phi(z')/V$ as the offer distribution.

We can solve the firm z's revenue, given the total amount of efficiency labor used for production, $h(z)$, which is determined by the amount of vacancies and employees' human capital. For tractability, we assume that the firm maximizes each period's total revenue without consideration of the impact of export destinations on workers' future human capital.

[27] Differing from papers that model both trade and wage dynamics (e.g., Fajgelbaum 2019, Dix-Carneiro et al. 2019), we introduce a set of foreign countries instead of one aggregated rest of world, because our empirical analysis shows that returns to experience depend on specific export destinations.

The firm's revenue maximization problem is:

$$\begin{aligned} \max_{\{I_n(z), y_n\}} r(z) &= \sum_n I_n(z) \left(y_n^{\frac{\sigma-1}{\sigma}} P_n Y_n^{\frac{1}{\sigma}} - P_1 f_n \right) \\ s.t. \ \sum_n I_n(z) \tau_n y_n &= z h(z) \end{aligned} \tag{7}$$

$y_n^{\frac{\sigma-1}{\sigma}} P_n Y_n^{\frac{1}{\sigma}}$ is the revenue if the firm sells y_n units of goods in market n, and $I_n(z) \in \{0, 1\}$ captures export decisions. $P_1 f_n$ is the value of fixed costs from selling to market n (P_1 is the home-market final-good price). The second equality is the resource constraint, meaning that the quantities sold (including iceberg costs of transportation) equal the firm's production. Given export decisions $I_n(z)$, we can solve the optimal quantities sold to each destination (proof provided in Appendix F.1):

$$y_n(z) = \frac{I_n(z) P_n^{\sigma} Y_n \tau_n^{-\sigma}}{\sum_{n'=1}^{N} I_{n'}(z) P_{n'}^{\sigma} Y_{n'} \tau_{n'}^{1-\sigma}} z h(z). \tag{8}$$

Then, equation (7) can be simplified as:

$$\max_{I_n(z)} r(z) = (z h(z))^{\frac{\sigma-1}{\sigma}} \left(\sum_{n=1}^{N} I_n(z) P_n^{\sigma} Y_n \tau_n^{1-\sigma} \right)^{\frac{1}{\sigma}} - P_1 \sum_n I_n(z) f_n. \tag{9}$$

In the case of convex vacancy costs ($\gamma_v > 0$), labor supply is no longer perfectly elastic at some wage level, and thus firms' export decisions are interdependent across destination markets. In total, there are $2^N - 1$ feasible combinations of destination markets. After choosing the optimal combination of export markets, the average revenue per efficiency unit is $a(z) = \frac{r(z)}{h(z)}$, which plays the role of labor productivity in our model, similarly as firm productivity in job search papers that assume one homogeneous good.

3.3 Wage Determination and Job Values

Wages are determined as piece-rate contracts. Consider a worker of age t with human capital h_t, employed at a firm z under a wage contract stipulating a piece rate of $0 \le r \le 1$, which represents the worker's share of total revenues and thus measures the degree of firm-worker rent sharing. If i_t efficiency units are devoted to human capital accumulation, he or she receives a wage $w = r a(z)(h_t - i_t)$, where $a(z)(h_t - i_t)$ is the total revenue generated by the worker. Denote the worker's value of this match as $V_t(r, h_t, z)$ and the joint (worker + firm) value as $M_t(h_t, z)$. The wage determination follows the generalized Nash bargaining in Dey and Flinn (2005) and Cahuc et al. (2006), as we now describe.

When the worker employed at current firm z is contacted by a poaching firm z', the firm who values the worker the most gets the worker. There are three cases. First, if the poaching firm values the worker more than the current firm, which means that $M_{t+1}(h_{t+1}, z') > M_{t+1}(h_{t+1}, z)$, the worker will move to the poaching firm. The new piece rate r' evolves as:

$$V_{t+1}(r', h_{t+1}, z') = M_{t+1}(h_{t+1}, z) + \beta \left(M_{t+1}(h_{t+1}, z') - M_{t+1}(h_{t+1}, z)\right). \tag{10}$$

The worker obtains the joint value of the match at the current firm plus a share β of the additional surplus by matching with the poaching firm.

In the second case, the poacher values the worker less than the current firm, but can offer the worker a wage that delivers a value higher than the worker's current value. This happens when $M_{t+1}(h_{t+1}, z') < M_{t+1}(h_{t+1}, z)$ but $M_{t+1}(h_{t+1}, z') > V_{t+1}(r, h_{t+1}, z)$. In this case, the worker stays in the current firm but will renegotiate its wage with the current firm, using the poacher as the outside option. The new piece rate r' evolves as:

$$V_{t+1}(r', h_{t+1}, z) = M_{t+1}(h_{t+1}, z') + \beta \left(M_{t+1}(h_{t+1}, z) - M_{t+1}(h_{t+1}, z')\right). \tag{11}$$

The worker can thus extract the full value of the job at the poaching firm plus a share of the additional surplus by matching with the current firm.

In the third case, if the poacher can not offer the worker a value higher than the worker's current value, the worker's wage does not change.

For an unemployed person who accepts a job from firm z, the starting wage w' satisfies:

$$V_{t+1}(r', h_{t+1}, z) = V^U_{t+1}(h_{t+1}) + \beta \left(M_{t+1}(h_{t+1}, z) - V^U_{t+1}(h_{t+1})\right). \tag{12}$$

Here $V^U_{t+1}(h_{t+1})$ is the value of an unemployed worker with human capital h_{t+1}. In the quantitative analysis, we follow Bagger et al. (2014) to assume that unemployment is equivalent to employment in the least productive firm: $V^U_{t+1}(h_{t+1}) = M_{t+1}(h_{t+1}, z_{\min})$. This assumption resolves the complication of allowing for heterogeneous reservation wages for workers of different human capital levels and ages.

We can also characterize the joint value of a job as follows:

$$
\begin{aligned}
M_t(h_t,z) &= a(z)(h_t - i_t) \\
&+ \frac{\kappa}{1+\rho} V^U_{t+1}(h_{t+1}) + \frac{\kappa\beta\lambda_U}{1+\rho}\int_{z_{\min}}^{z_{\max}} \max\{M_{t+1}(h_{t+1},z') - V^U_{t+1}(h_{t+1}),0\}dF(z') \\
&+ \frac{1-\kappa}{1+\rho} M_{t+1}(h_{t+1},z) + \frac{(1-\kappa)\beta\lambda_E}{1+\rho}\int_{z_{\min}}^{z_{\max}} \max\{M_{t+1}(h_{t+1},z') - M_{t+1}(h_{t+1},z),0\}dF(z').
\end{aligned} \tag{13}
$$

On the right-hand side of the equation, the first line captures the current-period's production value. The second line shows 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 and may also get an additional surplus if she can soon find a job. Finally, the last line captures the future value if an exogenous separation does not happen. In this case, the match either continues or enjoys an additional surplus if the worker is poached by a firm that values the worker better.

We assume that the choice of time spent on human capital accumulation follows the full-competition regime (Acemoglu and Pischke 1999) and maximizes the joint surplus. By using the first-order condition of equation (13), we obtain:

$$
i_t(h_t,z) = \left(\frac{\alpha\phi^E(z)}{a(z)}\frac{\partial M_t(h_t,z)}{\partial h_{t+1}}\right)^{\frac{1}{1-\alpha}}. \tag{14}
$$

Hence, the optimal time spent on human capital accumulation increases with marginal benefits, which are determined by the increment in human capital $\phi^E(z)$ and the marginal return of new human capital in production $\frac{\partial M_t(h_t,z)}{\partial h_{t+1}}$.

Finally, the optimal amount of vacancies $v(z)$ posted by the firm z is determined as:

$$
\begin{aligned}
c_v v(z)^{\gamma_v} P_1 &= \sum_{t=1}^{T} \frac{\lambda_U(1-\beta)}{V}\int \left[M_t(h_t,z) - V^U_t(h_t)\right] D^U_t(h_t)dh_t \\
&+ \sum_{t=1}^{T} \frac{\lambda_E(1-\beta)}{V}\int\int \max\{M_t(h_t,z) - M_t(h_t,z'),0\}D_t(h_t,z')dh_t d\Phi(z').
\end{aligned} \tag{15}
$$

Here $D^U_t(h_t)$ is the measure of unemployed workers with human capital h_t, and $D_t(h_t,z)$ is the measure of employed workers with human capital h_t and at firm z.[28] The left-hand

[28] We have $\sum_t \int D^U_t(h_t)dh_t = U$ and $\sum_t \int\int D_t(h_t,z)dh_t d\Phi(z) = 1-U$, which are defined after exogenous job separations but before job search.

side captures the marginal costs of posting a vacancy. The right-hand side captures the aggregate value 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.

3.4 General Equilibrium

The analysis so far focuses on the export activity of firms in the home country. To close the model, we assume that the home country imports a fixed number $\bar{M}^I$ of varieties with unit price p^I.[29] We abstract away from saving, and all the firm profits are spent on final goods. The balanced trade requires that when the goods market clears, firms' total export value equals the total value of imported varieties in the home country.

Now we define the general equilibrium of our model:

Definition 1 *The general equilibrium consists of meeting rates $\{\lambda_E, \lambda_U\}$ employment distribution $\{D_t^U(h_t), D_t(h_t, z)\}$, firms' selling decisions $\{y_n(z), I_n(z), a(z)\}$ and vacancy posting $v(z)$, the joint decision of human capital accumulation $i_t(h_t, z)$, and aggregate price and quantity variables in the home country $\{P_1, Y_1\}$. These variables satisfy:*
(a) meeting rates $\{\lambda_E, \lambda_U\}$ are determined by unemployment rate $U = \sum_t D_t^U(h_t)$ and the total amount of vacancies $V = \bar{M} \int v(z) d\Phi(z)$;
(b) employment distributions $\{D_t^U(h_t), D_t(h_t, z)\}$ are consistent with revenues $a(z)$, vacancies $v(z)$, and human capital accumulation $i_t(h_t, z)$;
(c) firms' selling decisions $\{y_n(z), I_n(z), a(z)\}$ are given by equation (7), given the amount of efficiency labor $h(z) = \sum_t \int D_t(h_t, z)(h_t - i_t(h_t, z))dh_t$ and aggregate price and quantities;
(d) firms' optimal vacancy postings $v(z)$ are given by equation (15);
(e) the joint decision of human capital accumulation $i_t(h_t, z)$ is given by equation (14); and
(f) aggregate price and quantity $\{P_1, Y_1\}$ clear the goods market in the home country.

3.5 Export Activity and Wage Profiles

In the model environment, wages of a worker at firm z can be written as:

$$\log w = \underbrace{\log h_t}_{\text{human capital}} + \underbrace{\log\left(1 - \frac{i_t}{h_t}\right)}_{\text{human capital investment}} + \underbrace{\log a(z)}_{\text{labor productivity}} + \underbrace{\log r}_{\text{piece rate}} \tag{16}$$

[29] The total value of imported varieties is given by $\bar{M}^I (p^I)^{1-\sigma} P_1^\sigma Y_1$.

Thus, a worker's within-job wage growth is:

$$\Delta \log w = \underbrace{\Delta \log h_t}_{\text{changes in human capital}} + \underbrace{\Delta \log \left(1 - \frac{i_t}{h_t}\right)}_{\text{changes in investment}} + \underbrace{\Delta \log a(z)}_{\text{changes in labor productivity}} + \underbrace{\Delta \log r}_{\text{changes in piece rate}} \tag{17}$$

Our model focuses on the steady state and does not incorporate dynamics in export status and labor revenues, as the model is computationally intractable when firms and workers are both forward-looking and need to form expectations of firms' future shocks when making decisions. When we quantitatively compute gains in experience returns immediately following export entry, we use a partial-equilibrium analysis similar to the recent literature (e.g., Buera, Kaboski and Yongseok 2021, Buera, Kaboski and Townsend 2021), by implementing alternative realizations of export costs to each firm in the steady state.

According to equation (17), export activity changes wage profiles within the firm through three channels. First, export activity affects workers' human capital increment, by shifting the mixture of workers' exposure to destinations' productive ideas, as shown by equation (6). If workers' human capital growth relies on the external environment ($\gamma_2 > 0$), and the knowledge stock λ_n varies across destination markets, then export activity can potentially produce large effects on workers' wage profiles through the human capital channel. Second, as a side effect of changes in human capital investment, workers' working time also changes. Finally, export activity can change workers' bargaining positions in the process of wage determination. In the model, foreign market access provides firms with opportunities to expand revenues. Because labor productivity changes are identical for young and old workers within a firm, they cancel out in our construction of wage profiles. However, increased revenues offer larger room for the current workers' wage to grow through wage renegotiations when poached, especially for young workers who are at the bottom of the job ladder.

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 *If meeting and separation rates $\lambda_U = 1$ and $\kappa = 1$, unemployment value $V_t = 0$,*[30] *discount rate ρ is large enough, and vacancy costs are linear $\gamma_v = 0$. The gains*

[30] This assumption can be justified by $z_{\min} \to 0$ or disutility of unemployment (Hornstein et al. 2011), though in the current model's quantitative analysis, we abstract from directly modelling the unemployment disutility by following Bagger et al. (2014) to conveniently assume that the unemployment value is equivalent

from trade are:

$$GT = \underbrace{\Pi_d^{-\frac{1}{\sigma-1}}}_{\textit{changes in real income per efficiency labor}} \times \underbrace{\frac{\bar{h}}{\bar{h}^{auc}}}_{\textit{changes in average efficiency labor per employee}} . \tag{18}$$

Π_d *is the home-country expenditure share on domestic goods in the observed economy.*

Proof: See Appendix F.2. □

We obtain Proposition 1 under several regularities 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). The assumption of unemployment value $V_t = 0$ and large discount rate ρ implies that firms obtain a proportion $(1-\beta)$ of revenues, and time spent on human capital accumulation is relatively small. The assumptions of $\gamma_v = 0$ implies that marginal costs of hiring remain constant, and thus export decisions across destinations are independent.

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 formula 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 et al. 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 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 that may benefit workers' human capital accumulation.

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 poachers. We will study the effects of wage renegotiations numerically.

to the employment value in the least productive firm, as discussed in Section 3.3.

4 Quantification

In this section, we calibrate our model to the Brazilian data. Then, through the lens of our quantitative model, we explore the determinants of the within-job wage profiles.

4.1 Data

We match the model to summary statistics from the employer-employee data and the customs data of the Brazilian formal manufacturing sector between 1994–2010. The core variables that we use are job-to-job transitions and the slope of wages on firm employment size. These variables are informative of the strength of workers' bargaining power and on-the-job search, thus governing the strength of wage renegotiations. Combined with this information, we use the within-firm wage profiles to inform the magnitude of human capital accumulation.

In our model, because of convex hiring costs, export decisions are interdependent across destination markets. To decide each firm's export decisions, we shall compare $2^N - 1$ feasible combinations of destinations for N markets, which is computationally demanding when N is large. We thus aggregate all destination markets (other than Brazil) by their continents and whether they are high-income countries. We obtain $N = 10$ groups of destinations, including Brazil, high-income countries in Europe, Asia, North America, and Oceania,[31] and non-high-income countries in Europe, Asia, North America, Africa, and South America.[32]

4.2 Calibration

To proceed, we must specify the function $\chi(\cdot)$ that determines the meeting rates between unemployed people and firms. It is common to use a Cobb-Douglas job matching function between searchers and vacancies (e.g., Shimer 2005), which implies $\chi(x) = c_M x^{\phi}$, where $0 < \phi < 1$ is the elasticity of job matches to vacancies. To capture that some small firms also export, we assume that time-invariant export fixed costs $\{f_n\}_{n=2,\ldots,N}$ follow a log-normal distribution, $\log f_n \sim \mathbb{N}(\log \bar{f}_n, \sigma_f)$, i.i.d. across firms and destinations. Our model abstracts from firm-level export stocks in each period, because modelling both labor market dynamics and stochastic changes in firm exports makes the model intractable.[33] Finally, it is common

[31] Africa and South America do not have high-income countries.

[32] Because non-high-income countries in Oceania accounted for a negligible share (less than 0.01%) of the Brazilian manufacturing exports in 2000, we omit them in the analysis.

[33] For example, in this case, the worker also needs to form expectations of firms' future export status when making moving decisions, and the firm will also need to take into account workers' different turnover rates

in the trade literature (e.g., Chaney 2008) to assume a Pareto productivity distribution $\Phi(z) = 1 - z^{-\zeta}$, with a larger shape parameter ζ implying less productivity dispersion.

The calibration must determine the following parameter values: each worker's lifetime T, discount rate ρ, the number of destinations N, the parameters of labor search processes and wage negotitation $\{\phi, c_M, \kappa, \eta, \beta\}$, human capital depreciation and returns $\{\delta_h, \alpha, \mu, \gamma_1, \gamma_2, \lambda_n\}$, the shape parameter ζ of productivity distribution, the elasticity of substitution across varieties σ, the demand and fixed costs of foreign markets $\{P_n^\sigma Y_n \tau_n^{1-\sigma}, \bar{f}_n, \sigma_f\}_{n=2,\ldots,N}$, the constant and curvature of vacancy costs $\{c_v, \gamma_v\}$, and import demand $\bar{M}^I (p^I)^{1-\sigma}$.

4.2.1 Parameters Set without Solving the Model

Table 4 lists the parameters set without solving the model. We calibrate a model of annual frequency and set the annual discount rate ρ to 0.04. Each individual works for 40 years, and therefore we set the total working time to $T = 40$ years. The number of destination markets is $N = 10$ as described above.

We set the elasticity of job matches to vacancies to $\phi = 0.3$ following Shimer (2005)'s estimate for the US economy, and this parameter value is commonly applied to other countries in the development literature (e.g., Feng et al. 2018). We follow Manuelli and Seshadri (2014) to use the depreciation of human capital $\delta_h = 0.02$ and the convexity in the production of human capital $\alpha = 0.48$. We proxy each country's knowledge stock λ_n by its GDP per capita in 2000 and aggregate them into our $N = 10$ groups of destination markets using Brazil's export value as weights. We normalize Brazil's knowledge stock to 1.

We set the elasticity of substitution across varieties $\sigma = 5$, which is the mean value in the trade literature (Head and Mayer 2014). For the convexity in vacancy costs γ_v, Dix-Carneiro et al. (2019) find γ_v to be 1.1 for Brazilian manufacturing firms.

4.2.2 Parameters Set by Solving the Model

We jointly estimate the remaining 29 parameters (listed in Table 5) to match 29 data moments on trade, labor market and wage profiles as listed in Table 6. To ensure consistency between the model-generated data and our empirical analysis, we compute experience returns (returns to 20 years of experience) in the model applying the same HLT method as discussed in Section 2.3. Importantly, we target the key empirical result—the increase in experience returns after export entry into high-income destinations—for which we use the

in their different export statuses.

Table 4: Parameters Set without Solving the Model

Parameter	Notation	Value	Source
Total working time (years)	T	40	
Discount rate	ρ	0.04	
Number of destination markets	N	10	Authors' computation
Elasticity of matches to vacancies	ϕ	0.3	Shimer (2005)
Depreciation of human capital	δ_h	0.02	Manuelli and Seshadri (2014)
Convexity in production of human capital	α	0.48	Manuelli and Seshadri (2014)
Stock of knowledge ($n = 1, ..., N$)	λ_n	1.99 (1.25)	Data on GDP per capita
Elasticity of substitution	σ	5	Head and Mayer (2014)
Curvature of vacancy costs	γ_v	1.1	Dix-Carneiro et al. (2019)

Notes: the value for the stock of knowledge is the average across $N = 10$ destination markets, with the standard deviation in parenthesis.

average of reduced-form evidence in Table 3. In the model, we implement alternative realizations of export fixed costs $\{f_n\}$ for each firm in the baseline equilibrium to compute short-run changes in experience returns immediately following export entry. As shown by equation (17), export entry leads to changes in the increment of human capital per time spent, changes in time allocated to human capital accumulation, and higher labor revenues that affect wage profiles by widening the scope of wage renegotiations.[34] We relegate the computation details to Appendix G.

To gain some intuition for how the parameters are determined, it is possible to see that some parameters have a more direct impact on specific moments. For example, export demand for destination n, $P_n^\sigma Y_n \tau_n^{1-\sigma}$, directly affects the share of sales to n in firms' total sales, and the average export cost, $\bar{f}_n$, determines the share of firms that export to destination n. The shape parameter of the productivity distribution ζ can be informed by the Pareto parameter of firm employment distribution (Axtell 2001). We infer the bargaining power β mainly from the slope of workers' wages on firm size, as a larger β implies that workers obtain higher shares of extra surplus in productive firms. And on-the-job search intensity η can be informed by the share of new hires that were employed in other firms (last year).

Finally, given the strength of wage renegotiations (mainly governed by workers' bargaining power β and on-the-job search intensity η), average experience returns are informative of the magnitude of human capital returns μ. The slope of experience returns on firm employment size and the change in experience returns due to export entry into high-income countries are informative of the dependence of human capital returns on firm productivity (γ_1) and the knowledge stock in destination markets (γ_2).

[34]Higher labor revenues do not directly affect wage profiles, as these changes are identical for young and old workers.

Table 5: Internally Calibrated Parameters

Parameter	Notation	Value
Constant in matching function	c_M	0.76
Job destruction rate	κ	0.16
On-the-job search intensity	η	0.12
Constant in human capital returns	μ	0.07
Constant in vacancy costs	c_v	0.06
Workers' bargaining power	β	0.60
Elast. of human capital returns to productivity	γ_1	0.18
Elast. of human capital returns to market knowledge	γ_2	0.29
Shape parameter of productivity distribution	ζ	3.40
Export demand (by destination, $n = 2, ..., N$)	$P_n^\sigma Y_n \tau_n^{1-\sigma}$	26.73 (28.94)
Export fixed costs (by destination, $n = 2, ..., N$)	$\bar{f}_n$	0.16 (0.12)
Std of export costs	σ_f	1.56
Import demand	$\bar{M}^I (p^I)^{1-\sigma}$	0.13

Notes: The values for export demand $P_n^\sigma Y_n \tau_n^{1-\sigma}$ and export fixed costs $\bar{f}_n$ refer to the average across $N = 9$ foreign markets, with the standard deviation in parenthesis. Because the demand depends on the normalization levels, we normalize the domestic price index to $P_1 = 1$ in the calibrated equilibrium.

4.3 Estimation Results

Table 5 presents the internally calibrated parameters. Our parameter values are reasonable compared with the literature. For example, our calibrated job destruction rate and on-the-job search intensity are 0.16 and 0.12 respectively, similar to 0.15 and 0.11–0.16 found in Fajgelbaum (2019) for Argentina manufacturing firms. Our calibrated wage bargaining power $\beta = 0.6$ is within the range of the estimates that use a bargaining model with wage renegotiations and human capital accumulation. For example, Bagger et al. (2014) find β to be between 0.29–0.32 for Danish firms, and Gregory (2019) estimates the bargaining power to be 0.66 using Germany firm data. Table 6 shows that our model almost exactly or very closely matches all the targeted moments.

4.4 Untargeted Moments

In Table 6, we compare several untargeted moments in the model to the data. Our model implies a slightly smaller exporter wage premium (0.10) than the one estimated by the RAIS data (controlling for individual fixed effects). 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.5.

Table 6: 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 (0.032)
Ratio of exports to firms' total sales, by destination ($N = 2, ..., 10$)	$\surd$	0.015 (0.023)	0.015 (0.023)
Ratio of imports to firms' total sales	$\surd$	0.14	0.13
Slope of num of export destinations on log firm employment	$\surd$	0.53	0.54
Labor Market Statistics			
Job finding rate (unemployed workers)	$\surd$	0.67	0.67
Vacancy filling rate	$\surd$	0.88	0.87
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	0.52
Pareto parameter of firm employment distribution	$\surd$	1.03	1.03
Unemployment rate		0.08	0.08
Wage Levels			
Slope of wages on log firm employment	$\surd$	0.05	0.05
Exporter wage premium		0.12	0.10
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	0.76
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	0.26
Changes in returns after entry into high-income destinations	$\surd$	0.23	0.20
Changes in returns after entry into non-high-income destinations		-0.02	-0.02

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 parenthesis. 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. (2019), 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 log 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 in the same way as in Section 2.3. Experience returns with regard to export entry are the average of reduced-form evidence in Tables 3 and D.5. When using the RAIS data, we apply the same restrictions as discussed in Section 2.1 to be consistent with our empirical analysis.

4.5 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 services 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.

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

Table 7: 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)	0.144***	0.169*	0.070***	0.105***
	(0.030)	(0.092)	(0.008)	(0.007)
Share of exporters		-0.169		-0.138***
		(0.548)		(0.046)
Obs	20	20	20	20
R-squared	0.833	0.833	0.935	0.959

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 are in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

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 20 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 20 equally sized bins and regress the logarithm of average time spent on human capital accumulation on log average firm size across bins.[35]

Table 7 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 elasticities of training intensity to firm employment size are slightly 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.[36]

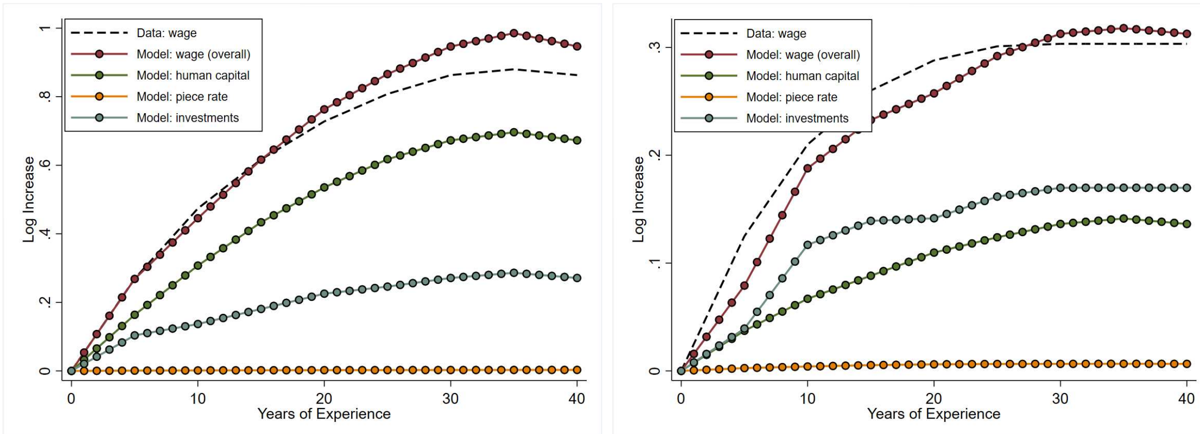
4.6 Decomposing the Returns to Experience

With the calibrated model, we now turn to understand what shapes the within-job wage profiles. Figure 4a presents the average experience-wage profile across firms and the decom-

[35]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 across firms, and thus firms that enjoy larger benefits from human capital accumulation will also perform more of it in the extensive margin. This extension is beyond the scope of this paper.

[36]For example, in the 1995 US 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.

Figure 4: Decomposing the Returns to Experience



(a) Overall Wage-experience Profiles　　**(b)** Difference btw Exporters/non-exporters

Notes: The data on experience returns are computed according to Section 2.3. We report the (unweighted) average experience-wage profiles across firms in Figure 4a and the (unweighted) average differences between exporters and non-exporters in Figure 4b.

Table 8: Changes in Returns to 20 Yrs of Experience due to Export Entry

	Data	Model	Model-based Decomposition		
			Human Capital	Piece Rate	Investment
Entry into high-income destinations	0.23	0.20	0.08 (43%)	0.01 (5%)	0.10 (52%)
Entry into non-high-income destinations	-0.02	-0.02	-0.01 (35%)	0.00 (-5%)	-0.02 (70%)

Notes: The data on experience returns with regard to export entry is the average of reduced-form evidence in Table 3 and D.5. The percentage in brackets refers to the contribution of each channel to the overall model-generated change.

position of it into different factors. We find that human capital contributes the most to within-job wage profiles, followed by changes in human capital investment (working time). The contribution of wage renegotiations is small, because in our calibrated model with low on-the-job search intensity, workers are not poached very often, and those poached workers with very good offers would leave the firm (not reflected by within-job wage profiles). Figure 4b presents the decomposition of differences in experience-wage profiles between exporters and non-exporters. We still find that human capital is an important factor behind the difference. However, because of the diminishing returns of human capital investment, the contribution of human capital relative to investment becomes smaller.

Table 8 presents the decomposition of changes in returns to experience due to export entry. Similar to what we found in Figure 4, changes in piece rates contribute little to changes in returns. Moreover, as expected, export entry to high-income countries is associated with higher human capital accumulation. However, because of the diminishing returns of human capital investment, the contribution of human capital to changes in experience returns due to export entry is smaller than the overall role of human capital in experience returns found in Figure 4a. 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 investment, and higher revenues per labor following export entry also increase the opportunity costs of investing in human capital.

Our quantitative model finds a small role of changes in firm-worker rent sharing in explaining the wage profiles, in line with evidence in Arellano-Bover and Saltiel (2021) who find that in Brazil, returns to experience are not much different between all workers and the sample of displaced workers who lose previous 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' wage to grow through wage negotiations when poached. In Section 5.4, we show that with a low value of workers' wage bargaining power, the role played by changes in firm-worker rent sharing in determining wage profiles becomes much more important.

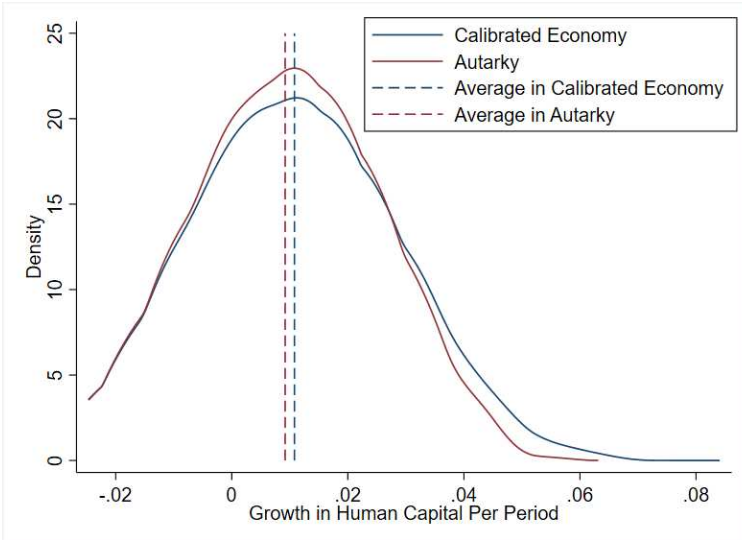
5 Counterfactual Exercises

In this section, we use our calibrated model to understand the quantitative effects of trade openness and how the aggregate implications depend on the destination's stock of knowledge. We also show that changes in foreign knowledge stock can affect domestic workers' human capital accumulation. Finally, we provide robustness checks regarding model assumptions and parameters.

5.1 Gains from Trade

We report the gains from trade in Table 9. The aggregate change in real income from autarky to the calibrated economy is 9.50%. Consistent with Proposition 1, both more human capital and higher real income per efficiency labor contribute to the gains from trade, with a 4.86% and 4.63% increase in real income respectively. As we allow for unemployment quantitatively, trade openness increases firms' overall vacancy postings, which also leads to a 0.52% employment gain. Finally, as workers invest more efficiency units in human capital, the average working time (one minus the share of human capital investment in total human

Figure 5: Distribution of Human Capital Growth



capital) decreases by 0.53% after trade openness.

Table 9: Gains from Trade

Changes in Real Income from Autarky to the Calibrated Economy			9.50%
Decomposition:			
	Real Income Per Employee		
Employment	Income Per Efficiency Labor	Human Capital	Investment
0.52%	4.63%	4.86%	-0.53%

Our results point to the important role of human capital in shaping the gains from trade. Figure 5 plots the growth in human capital per period across all the workers in the autarkic and the calibrated economies. We find that trade openness shifts the distribution of human capital increase to the right, indicating faster human capital after trade openness.

Motivated by decomposition of productivity growth (Foster et al. 2001), we further decompose changes in human capital accumulation to reflect the contributions of different forces. Denote the average growth of human capital per period in the economy as g_h.

$$g_h = \int l(z) g_h(z) d\Phi(z), \tag{19}$$

where $l(z)$ is firm z's employment share, and $g_h(z)$ is average growth in human capital per

Table 10: Changes in Human Capital Growth

(a) Changes in human capital growth from autarky to the calibrated economy			
Overall	Within-firm Term	Between-firm Term	Cross-firm Term
0.16%	0.12%	0.01%	0.03%
(b) Within-firm term by firms' status in the calibrated economy			
Non-exporters	Exporters (High-income)	Exporters (Non-high-income)	Exporters (Both Dests)
-0.03%	0.03%	-0.02%	0.14%

period at firm z. Thus, the changes in growth of human capital can be written as:

$$g_h^{'} - g_h = \int \underbrace{l(z)[g_h^{'}(z) - g_h(z)]}_{\text{within-firm term}} + \underbrace{[l^{'}(z) - l(z)][g_h(z) - g_h]}_{\text{between-firm term}} + \underbrace{[l^{'}(z) - l(z)][g_h^{'}(z) - g_h(z)]}_{\text{cross-firm term}} d\Phi(z) \tag{20}$$

The first term captures within-firm changes in human capital growth, whereas the second term represents reallocating employment given the initial human capital growth. The third term represents the cross effect of reallocation and changes in the human capital growth.

Table 10 reports the results. We find that the within-firm term contributes the most to the overall increase in human capital growth from autarky to the calibrated economy. Panel (B) of Table 10 further decomposes the within-firm term according to firms' export status in the calibrated economy. We find that firms that export to both high-income and non-high-income destinations contribute the most to the increase in the within-firm term, as they are large in employment size and gain higher human capital returns after trade openness. The contribution of firms that export solely to both high-income is relatively small, as they make up small employment shares. Non-exporters and exporters that only sell to non-high-income countries contribute negatively to the within-firm term.[37]

5.2 Changes in Trade Costs

In Table 11, we report changes in real income and human capital after a 10% decline in Brazil's export trade costs to high-income and non-high-income destinations respectively. We find that lowering trade costs to high-income destinations by 10% would increase Brazil's real income by 2.70%, which is largely due to a 2.12% increase in workers' average human capital. Surprisingly, lowering trade costs to non-high-income destinations by 10% would

[37]Numerically, non-exporters and exporters that only sell to non-high-income countries only slightly change human capital investment after trade openness. However, since their hires' average human capital is higher (due to general equilibrium effects) after trade openness, the contribution of these firms to the human capital growth becomes smaller.

Table 11: Gains from 10% Decline in Export Iceberg Costs

Export destinations	Export Output	GDPPC (Brazil=1)	10% Decline in Trade Costs Δ%Real Income	Δ%Human Capital
By income levels:				
High-income	0.081	3.58	2.70%	2.12%
Non-high-income	0.053	1.10	-0.21%	-0.73%
By main export destinations:				
Euro & US	0.070	3.60	2.81%	1.96%
China (2019)	0.069	1.19	0.18%	-0.32%
South America	0.032	1.12	-0.12%	-0.43%

reduce Brazil's real income by 0.21%. This reduction is mainly driven by a 0.73% decline in workers' average human capital, as higher demand from non-high-income destinations makes productive firms to reallocate labor away from high-income export destinations, and higher revenues per labor due to exporting also increase the opportunity costs of investing in human capital in the presence of hiring constraints. It is worth noting as we can not solve the transitional dynamics, it is possible that lowering trade costs to non-high-income destinations leads to gains in the short-run due to changes in wages and prices.

In the last three rows of Table 11, we report changes in real income and human capital after a 10% decline in Brazil's export trade costs to main export destinations respectively.[38] In line with our previous results on high-income countries, lowering trade costs to Europe and the US would lead to large gains in real income, which are mainly driven by gains in workers' human capital. On the other hand, the wage and price gains from lowering trade costs to China or South America are largely offset by reductions human capital levels.

5.3 Changes in the Knowledge Stock

Table 12 reports changes in real income and human capital after a 10% increase in Brazil's trade partner's knowledge stock. We find that higher knowledge stocks from trade partners would increase Brazil's real income, mainly through increases in workers' average human capital. Moreover, the increase is larger if the trade partners are high-income countries as

[38] Our baseline model is calibrated to the export data in 2000, in which year non-high-income countries in Asia (mainly China) were still a relatively small export destination for Brazil. Brazil's exports to China grew very fast over the recent decades (Appendix A.1), and there has been a heated discussion regarding the trade agreement between China and Brazil in recent years. In the counterfactual exercise regarding China, we first recalibrate the demand and the knowledge stock of non-high-income countries in Asia to match Brazil's export-to-output ratio to China and the relative GDP per capita between China and Brazil in 2019.

Table 12: Gains from 10% Increase in Trade Partners' Knowledge

Export destinations	Export Output	GDPPC (Brazil=1)	10% Increase in Knowledge Stock	
			Δ%Real Income	Δ%Human Capital
By income levels:				
High-income	0.081	3.58	0.51%	0.51%
Non-high-income	0.055	1.10	0.12%	0.12%
By main export destinations:				
Euro & US	0.070	3.60	0.42%	0.44%
China (2019)	0.069	1.19	0.13%	0.20%
South America	0.032	1.12	0.08%	0.08%

these countries have higher initial knowledge stocks (thus the increase in knowledge stocks in terms of absolute values is larger). Our model thus indicates that workers' human capital accumulation may reflect changes in international knowledge diffusion.

5.4 Robustness Checks

We present robustness checks regarding our baseline calibration using different parameter values and assumptions. In each case, we recalibrate the model parameters to match the targeted moments and then compute the gains in real income and human capital from trade.[39]

5.4.1 Alternative Parameterization

Table 13 reports the gains from trade, by using different parameter values. In the first exercise, we change the depreciation rate of human capital from $\delta_h = 0.02$ in the baseline to $\delta_h = 0.01$, as suggested by evidence on the lifecycle 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 face stronger diminishing returns and result in a slightly smaller increase in average human capital.

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 US (Faberman et al. 2017). A larger on-the-job search intensity speeds up workers' reallocation toward firms that are more productive and

[39] In the case of changing model parameters, by fixing one endogenously calibrated parameter, our model usually mismatches the most relevant targeted moment related to the fixed parameter value in the recalibration. For instance, by changing workers' bargaining power to $\beta = 0$, our model is unable to generate the positive slope of wages on firm size as shown in the data.

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 find that allowing for a larger on-the-job search intensity largely 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 (2019). 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 becomes smaller.

For each exercise, the last three columns in Table 13 also 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' wage 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 poachers as the outside option to gain better bargaining positions.[40] With the same logic, as most workers already have good bargaining positions in the baseline calibration, changing on-the-job search intensity (poaching rate) has little impact on the contribution of wage negotiations, whereas higher on-the-job search intensity mostly leads to more job-job transitions.[41]

5.4.2 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 (e.g., Arrow 1962, Hopenhayn 1992). Appendix Section H presents the model extension to consider that all human capital comes from learning-by-doing, and that the human capital processes can potentially vary across firms and ages (e.g., Bagger et al. 2014, Gregory 2019).

[40] As shown in Section 3.3, if the joint surplus of the job at poachers 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.

[41] The share of new hires that were employed in other firms (last year) increases from 51% in the baseline model ($\eta = 0.12$) to 64% when assuming $\eta = 0.4$, indicating more job-to-job transitions with higher on-the-job search intensity.

Table 13: Robustness Checks

	Gains from Trade		Decomposing ΔExperience Returns (after entry into high-income dests)		
	Δ%Real Income	Δ%Human Capital	Human Capital	Piece Rate	Investment
(1) Baseline	9.50%	4.86%	43%	5%	52%
Alternative parameterization:					
(2) HC depreciation rate $\delta_h = 0.01$	8.75%	4.03%	45%	6%	49%
(3) On-job search intensity $\eta = 0.4$	12.82%	8.54%	44%	5%	52%
(4) Workers' bargaining power $\beta = 0$	9.07%	4.41%	38%	56%	6%
Alternative assumptions:					
(5) Learning-by-doing	17.92%	11.02%	93%	7%	0%

Notes: 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 8.

We recalibrate the model with learning-by-doing and have two findings. First, the model with learning-by-doing cannot produce the (untargeted) negative experience returns from entry to non-high-income destinations. Even though non-high-income destinations on average have higher GDP per capita (knowledge stock) than Brazil, in our baseline model, export revenues also raise opportunity costs of human capital investment, which reduces human capital investment and thus reduces the experience returns from entry to non-high-income destinations. However, this change in opportunity costs of human capital accumulation is missing in the model with learning-by-doing. In this sense, our baseline model with endogenous human capital investment matches the data better.

Second, the gains in human capital from trade openness are 11.02% in the model with learning-by-doing, compared with 4.86% in the baseline model. Although it is difficult to quantitatively determine the portions of human capital coming from investment and learning-by-doing, we view these two results as informative of upper and lower bounds of the gains in human capital from trade. With costless human capital accumulation, the model with learning-by-doing 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, with all human capital arising from endogenous investment, our baseline model attributes one-half of differences in wage profiles between exporters and non-exporters to changes in time allocated to human capital growth (Figure 4) and thus provides a lower bound for the gains in human capital from trade.

6 Conclusion

Using Brazilian employer-employee and customs data, this study documents that workers' within-job lifecycle wage growth is faster at exporters than at non-exporters. Apart from selection of firms with higher returns to experience into exporting, we find that workers enjoy steeper experience-wage profiles when firms export to high-income destinations. To quantitatively understand the interaction between export markets and workers' wage profiles, we develop and quantify a model in which firms meet workers by random search and decide whether to perform export activity. In the model, workers' within-job wage grows due to human capital growth, changes in time allocated to human capital accumulation, and wage renegotiations. We find that human capital growth can explain roughly 40% of differences in wage profiles between exporters and non-exporters as well as the gains in experience returns after entry into high-income destinations. We show that the increased human capital per worker accounts for one-half of the overall gains in real income from trade openness. We also show that the effects of trade liberalization depend on trade partners. In particular, lowering export costs might lower workers' human capital and reduce the gains from trade if the trade partners are low-income destinations.

Understanding the effects of trade on workers' wages is important because of its implications for aggregate welfare and inequality. We view this study as one of the first steps to empirically and quantitatively understanding the effects of trade on workers' lifecycle wage growth. Our results indicate that workers' human capital accumulation may interact with destination markets. A fruitful area for future study is how this interaction impacts the effects of globalization on workers' income levels and inequality in countries with different development levels.

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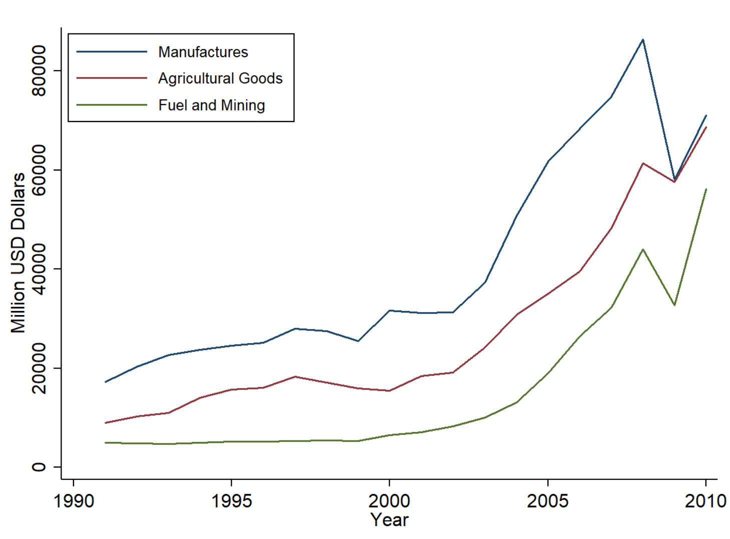
Appendix for Online Publication

A The Brazilian Economy

A.1 Brazilian Trade Patterns

Up to the 1990s, Brazil was a relatively closed economy to international trade. In the 1990s, with the economic liberalization, reductions in import tariffs, and the Mercosur Trade Agreement, Brazil started to open to international trade. After 1999, exports started to increase substantially due to changes in the exchange rate regime and the large devaluation episode. This process sped up after 2002, with a new depreciation episode and an improvement of international agricultural prices. Table A.1 shows the trends of exports for manufacturing goods, agricultural goods, and fuel over our sample period. It is clear that there was a sharp increase in exports after 2000, and that manufacturing goods represented a large share of Brazil's exports.

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



Note: 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.

Moreover, Rocha et al. (2008) explain how Brazil's exports are highly diversified across a variety of products. Apart from agriculture, Brazil intensively exports chemical products, pharmaceutical products, aircrafts, automobiles, and home appliances. In 2004, there were more than 10,000 different 8-digit HS products exported by more than 15,000 firms.

Table A.1 presents the share of Brazil's exports to each destination. In the 1990s, thanks to the Mercosur agreement, there was an increase in the share of exports destined to Latin American countries, in particular Argentina to which its share increased from 2% in 1990 to

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

Note: 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.

11% in 2000. While the U.S. was the biggest markets for Brazilian exporters in 1990 with 25% of total exports, this 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 around half of total exports going to developed economies (e.g., the U.S., Eurozone, Japan) and half going to other developing economies.

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 took place with a rapid increase in GDP, improvements in social-economic indicators, and a considerable decrease in the amount of unemployment and unregistered workers. For an extensive review of policies and the background about the

Table A.2: Exports by Products

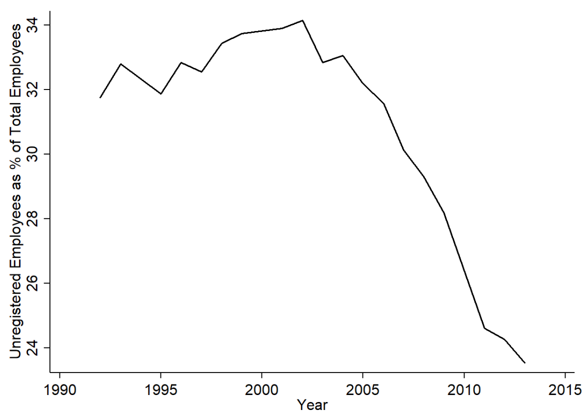
	Product Share (%)		Value (U.S.$ Mill)		RCAI	
	1990	2010	1990	2010	1990	2010
By Type						
Raw materials	21.37	41.93	6713	84671	1.84	2.93
Intermediate goods	39.01	27.29	12252	55109	1.75	1.28
Consumer goods	20.81	14.62	6537	29517	0.56	0.44
Capital goods	15.45	14.27	4854	28822	0.35	0.42
By Product						
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

Note: 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 2010 and 1990. The data is collected from WITS (World Integrated Trade Solution). The products and products types are ranked by the share of exports in 2010.

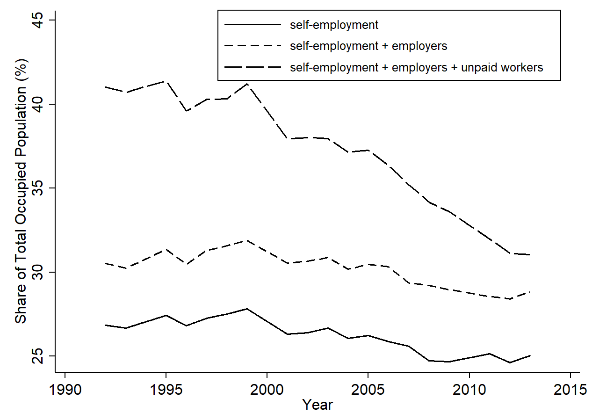
informal sector in Brazil, see Dix-Carneiro et al. (2019).

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 2010's. 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. Because the data is only available for two years, we are not able to apply the HLT method. As some reference, we draw the experience-wage profiles in the cross section. Figure A.3a plots both profiles and shows that formal workers have stepper experience-wage profiles than informal workers.

Moreover, besides formal and informal employees, Brazilian employment also includes self-employed workers, employers, and unpaid workers, and these three types of employment may not appear in RAIS (except for employers who receive a wage). Figure A.2b shows the share of self-employed workers, employers and unpaid workers in Brazilian total employment.



(a) Share of Informal Employees



(b) Share of Non-employees in Occupied Pop

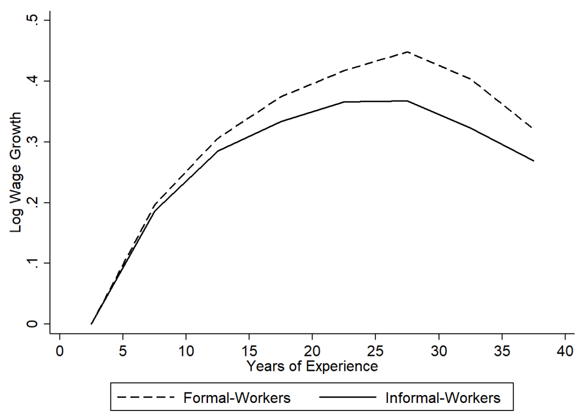
Note: The left-hand figure shows the share of unregistered employees in total employees. The data comes from the PNAD censuses. In the right-hand panel, the share of self-employed people represents the ratio of the amount of self-employed workers to total occupied population. The share "+ employers"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

These three types of employment represented 30–40% of Brazilian employment in the 90's and 2000's. We use 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 2.2, because we cannot identify the same individuals in multiple rounds of 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 in 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. (2019) show that within tradable sectors, most of workers are formally employed. 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 infomral 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). Establishments receive 14-digit unique permanent tax codes (CNPJ), from which we can identify firms by the first 8 digits of the code (Muendler et al. 2012). We focus



(a) Informal and Formal Workers

(b) Wage and Self-employed Workers

Note: 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.

on firms and aggregate establishments into the affiliated firms. Firms are mandated by law to annually provide workers' information to RAIS, and thus the data contains annual information on all workers employed in the Brazilian formal sector. 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 et al. (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 to merge the RAIS data with Brazilian customs declarations for merchandise exports collected at SECEX (Secretaria de Comércio Exterior) for the years 1994–2010, following Aguayo-Tellez et al. (2010). 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. We also have detailed data on export value and quantity by 8-digit HS products and destinations for the years 1997–2000.

B.1 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-educ}). In each year, we obtain experience-wage profiles by computing the average log hourly wage for workers in each 5-year experience bin $x \in X$ ={1–5,6–10,...,36–40}, separately for workers observed in exporting and non-exporting firms. Because we are interested in lifecycle 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.1, 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 0.74 (0.49) higher than workers with 1–5 years of experience.[42] This pattern holds in different time periods (Columns (2)–(3)). 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 better workforce), in Panels B to D of Table B.1, 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. 2018, 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),[43] and in larger firms (Panel D). Moreover, we find that within all of these categories, workers have higher lifecycle 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. With this suggestive pattern in mind, we formally estimate experience-wage profiles in Section 2.2.

[42] Our results are comparable to Lagakos et al. (2018) who use 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)).

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

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

	(1)	(2)	(3)	(4)	(5)
	Panel A: Aggregate profiles				
				Rel. to non-exporters' first bin	
	all	1994–2000	2001–2010	first bin	40 years of exp
Exporter	0.74	0.67	0.79	0.29	1.04
Non-Exp	0.49	0.48	0.51	0	0.50
Difference	0.25	0.19	0.28	0.29	0.54
	Panel B: Aggregate profiles by education level				
	illiterate	primary	middle school	high school	college
Exporter	0.22	0.69	0.84	1.29	1.43
Non-Exp	0.18	0.46	0.55	0.82	1.08
Difference	0.04	0.23	0.29	0.47	0.35
	Panel C: Aggregate profiles by occupation				
	professionals	technical	other white-collar	Skilled blue-collar	unskilled blue-collar
Exporter	1.10	0.99	0.52	0.57	0.23
Non-Exp	0.85	0.71	0.34	0.44	0.16
Difference	0.25	0.28	0.18	0.13	0.07
	Panel D: Aggregate profiles by firm size				
	10-50	50-100	100-500	500-1000	1000+
Exporter	0.55	0.61	0.69	0.77	0.81
Non-Exp	0.43	0.50	0.59	0.58	0.47
Difference	0.12	0.11	0.10	0.19	0.34

Note: 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 (4)–(5) of Panel A use the average log wage of workers with 1–5 years of experience at non-exporters as normalization.

C Empirical Method and Additional Results

C.1 HLT Method

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

$$\Delta \log(w_{it}) = \sum_{x \in X} \phi_s^x D_{it}^x + \zeta_{st} + \epsilon_{it}. \tag{C.1}$$

The collinearity problem is that for each time t, $\zeta_{st} = 1$ is perfectly correlated with $\sum_x D_{it}^x = 1$, 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:

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

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

$$\Delta \log(w_{it}) = \sum_{x \in X} \phi_s^x D_{it}^x + g_s + (e_{st} - e_{st-1}) + \epsilon_{it}. \tag{C.3}$$

We then restrict cyclical components to average zero over the time period $\sum_t e_{st} = 0$ and to be orthogonal to a time trend $\sum_t e_{st} t = 0$. These two restrictions reduce the freedom of $\{e_{st}\}$ by two and resolve the collinearity problem of time and experience returns (e_{st} and $\sum_x D_{it}^x$), as also used in Deaton (1997) and Aguiar and Hurst (2013) in estimating lifecycle 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 $\{\gamma_{st}\}$ into trends $\{\zeta_{st}\}$, 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 et al. (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 subscript 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 difference between exporters and the appropriate control group can be captured by a set of observables $X_{\omega,t}$. Specially, we first estimate each firm's probability $Pr(X_\omega)$ to start to export as a function of observables $X_{\omega,t}$ 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,

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

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. $W(\omega, \omega')$ is the weight of each non-exporter ω' in constructing the control group, with $\sum_{\omega' \in C_p \cap I_0} W(\omega, \omega') = 1$ 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 which 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,

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

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).

C.3 Panel Estimation of Workers' Experience Effects

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

$$w_{ikt} = \theta_k s_i + \sum_{x \in X} \sum_{k' \in \{e,n\}} \phi^x_{k'} exp^x_{ik'} + \mu_i + \gamma_{kt} + \epsilon_{ikt}, \tag{C.7}$$

where i, k and t represent individual, type of firms, and time, separately. w_{ikt} is the log wage for an individual i currently working in type-k firms $k \in \{e, n\}$, either exporters (e) or non-exporters (n). The variable s_i represents schooling, the returns of which can depend on the current firm type. The variable $exp^x_{ik'}$ denotes her 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 $exp^x_{ik'}$ on current wages. We let $\phi^x_{k'}$ differ across experience bins so that experience returns vary across different stages of life. γ_{kt} is a vector of time effects specific to firm types; and μ_i is a vector of individual fixed effects.

To proceed with estimation of our regression in equation (C.7), 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 under 25 years old[44] and construct their full employment history 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'

[44]This aims to rule out old workers for whom we do not observe their previous employment histories, particularly those who started work before 1986 or were employed in the informal sector in their early life.

wages to be within a job, we can explore how experience affects wages after switching firms.

Column (1) of Table C.1 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 10.2% wage premium relative to a job at non-exporters. If she continues to work at exporters, she would enjoy a 16.5% higher wage growth than working at non-exporters over 20 years of experience, in line with our estimation results in Section 2.2.

Column (2) introduces the years of working at exporters/non-exporters in the same firm as the current firm into regression (C.7), 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 report the coefficients on the years of working at non-exporters in the same firm as the current firm. We do 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 in an exporter, she would enjoy a 10.5% higher wage than previously working at non-exporters for 20 years.

In Column (3) of Table C.1, 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 (C.7), 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 15% higher wage growth 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 2.

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 et al. 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 15% higher post-displacement earnings than previously working at exporters that only export to non-high-income destinations.

Table C.1: Dependent Variable: Log Hourly Wage (Current Year)

	All Young Workers			Displaced Young Workers		
	(1)	(2)	(3)	(4)	(5)	(6)
Schooling	0.000***	0.001***	0.000***	0.058***	0.059***	0.058***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Schooling × Exporter	0.006***	0.006***	0.006***	0.020***	0.020***	0.020***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Exporter	0.048***	0.027***	0.048***	-0.023***	-0.025***	-0.024***
	(0.001)	(0.001)	(0.001)	(0.008)	(0.009)	(0.008)
Years of working at exporters	0.104***	0.080***	0.102***	0.086***	0.087***	0.094***
(1–5 years of work history)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Years of working at non-exporters	0.093***	0.079***	0.093***	0.060***	0.060***	0.060***
(1–5 years of work history)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Years of working at exporters	0.053***	0.030***	0.050***	0.064***	0.064***	0.062***
(6–10 years of work history)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Years of working at non-exporters	0.044***	0.025***	0.044***	0.044***	0.045***	0.044***
(6–10 years of work history)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Years of working at exporters	0.032***	0.019***	0.028***	0.049***	0.047***	0.040***
(11–15 years of work history)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
Years of working at non-exporters	0.026***	0.012***	0.026***	0.026***	0.026***	0.025***
(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***	0.012***	0.022***	0.023***	0.020***	0.017***
(16–20 years of work history)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.005)
Years of working at non-exporters	0.017***	0.004***	0.017***	-0.014***	-0.016***	-0.013***
(16–20 years of work history)	(0.001)	(0.001)	(0.001)	(0.004)	(0.005)	(0.004)
Years of working at exporters (1–5 years)		0.022***			0.008***	
& in same firm as current firm		(0.001)			(0.002)	
Years of working at exporters (1–5 years)			0.008***			-0.018***
× ratio of #high-income dests			(0.001)			(0.002)
Years of working at exporters (6–10 years)		0.026***			0.009***	
& in same firm as current firm		(0.001)			(0.002)	
Years of working at exporters (6–10 years)			0.007***			0.009***
× ratio of #high-income dests			(0.001)			(0.003)
Years of working at exporters (11–15 years)		0.016***			0.015***	
& in same firm as current firm		(0.001)			(0.005)	
Years of working at exporters (11–15 years)			0.009***			0.024***
× ratio of #high-income dests			(0.001)			(0.005)
Years of working at exporters (16–20 years)		0.014***			0.029***	
& in same firm as current firm		(0.001)			(0.011)	
Years of working at exporters (16–20 years)			0.006***			0.015
× ratio of #high-income dests			(0.001)			(0.010)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Worker fixed effects	Yes	Yes	Yes			
Observations	41,793,680	41,793,680	41,793,680	293,462	293,462	293,462
R^2	0.863	0.865	0.863	0.487	0.488	0.488

Note: 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). Robust standard errors are in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

D Additional Tables

Table D.1: 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***	0.031	-0.008	-0.055	-0.111	-0.081
	(0.013)	(0.030)	(0.036)	(0.075)	(0.127)	(0.126)
Exporter × ratio of # high-income to # total dests			0.126***	0.231**		
			(0.053)	(0.112)		
Exporter × share of exports to high-income dests					0.175*	
					(0.105)	
Exporter × log(avg GDPPC of dests)						0.126**
						(0.063)
Exporter × log(# total dests)			0.004	0.043	0.024	0.025
			(0.021)	(0.053)	(0.060)	(0.060)
Exporter × log(avg exports per employee)					0.015	0.013
					(0.022)	(0.022)
Duration of workers' previous experience at exporters		-0.090***	-0.084***	-0.259**	-0.260**	-0.260**
		(0.023)	(0.023)	(0.106)	(0.106)	(0.106)
Duration of workers' previous experience at exporters (high-income dests)		0.061**	0.052*	-0.064	-0.067	-0.067
		(0.028)	(0.028)	(0.122)	(0.122)	(0.122)
Duration of firms' previous export participation		0.017	0.013	0.127*	0.132*	0.128*
		(0.012)	(0.012)	(0.070)	(0.070)	(0.071)
Duration of firms' previous export participation (high-income dests)		-0.016	-0.011	0.019	0.012	0.015
		(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	344,785	344,785	344,785	77,888	77,888	77,888
R-squared	0.007	0.318	0.318	0.488	0.488	0.488

Note: This table presents estimates from regressions of firm-year-level returns to 20 years of experience on firm characteristics. The baseline group is non-exporters. The controls are the shares of high-school and cognitive workers in the firm's workforce as well as firm size. Robust standard errors are 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).

Table D.2: Wage Profiles and Firm Characteristics

	Dep Var: Firm-year-level Returns to 20 Yrs of Experience					
	(1)	(2)	(3)	(4)	(5)	(6)
	manufacturing					
Industry group	differentiated		non-differentiated		agri & mining	
Period	94–10	97–00	94–10	97–00	94–10	97–00
Exporter	-0.005	-0.107	-0.027	0.053	0.295	-0.757
	(0.055)	(0.254)	(0.046)	(0.211)	(0.187)	(0.542)
Exporter × ratio of # high-income to # total dests	0.251***	0.432*	0.046	0.178	-0.225	-0.178
	(0.084)	(0.245)	(0.067)	(0.175)	(0.226)	(0.433)
Exporter × log(# total dests)	-0.003	0.014	-0.015	0.002	-0.017	0.264
	(0.032)	(0.123)	(0.026)	(0.095)	(0.099)	(0.224)
Exporter × log(avg exports per employee)		0.024		-0.010		0.113
		(0.044)		(0.035)		(0.078)
Industry, Year and Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs	153,733	36,008	189,564	43,355	87,035	20,954
R-squared	0.337	0.533	0.333	0.544	0.308	0.428

Note: This table presents regressions of firm-year-level returns to 20 years of experience on firm characteristics. The baseline group is non-exporters. The controls are the shares of high-school and cognitive workers in the firm's workforce as well as firm employment size. Robust standard errors are in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Table D.3: Labor Composition for New Exporters to High-income Destinations

Post-exporting period	0	1	2	3
(a) Outcome: share of high-school grads				
Export entry	0.008	0.019**	0.024***	0.036***
	(0.006)	(0.008)	(0.009)	(0.010)
Nr treated	4,164	2,191	1,693	1,477
Nr controls	158,734	118,285	93,056	75,150
(b) Outcome: share of cognitive occupations				
Export entry	-0.001	-0.005	0.004	0.000
	(0.005)	(0.006)	(0.007)	(0.008)

Notes: The table reports the difference of labor composition 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—returns to 20 years of experience, the shares of high-school and cognitive workers, firm size, and export status to non-high-income destinations, as well as 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%.

Table D.4: Returns to 20 Years of Experience of New Exporters to High-income Destinations (for Export Exiters in Post-exporting Periods)

Post-exporting period	1	2	3
(a) Outcome: returns to experience			
Export entry	-0.012	0.120	0.041
	(0.130)	(0.110)	(0.102)
Nr treated	1,466	1,552	1,416
Nr controls	106,910	93,695	75,061
(b) Outcome: growth in returns (relative to $\tau = -1$ period)			
Export entry	0.057	0.276*	0.125
	(0.180)	(0.156)	(0.156)

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—returns to 20 years of experience, the shares of high-school and cognitive workers, firm size, and export status to non-high-income destinations, as well as 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%.

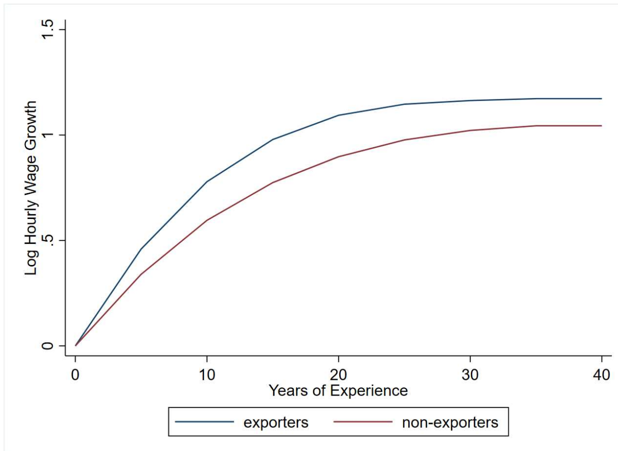
Table D.5: Returns to 20 Years of Experience of New Exporters to Non-high-income Destinations

Post-exporting period	0	1	2	3
(a) Outcome: returns to experience				
Export entry	0.014	-0.004	-0.085	-0.023
	(0.077)	(0.091)	(0.120)	(0.111)
Nr treated	4,656	2,629	2,072	1,767
Nr controls	136,986	100,340	78,052	62,229
(b) Outcome: growth in returns (relative to $\tau = -1$ period)				
Export entry	-0.023	-0.027	0.047	-0.031
	(0.110)	(0.131)	(0.167)	(0.164)

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—returns to 20 years of experience, the shares of high-school and cognitive workers, firm size, and export status to high-income destinations, as well as 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%.

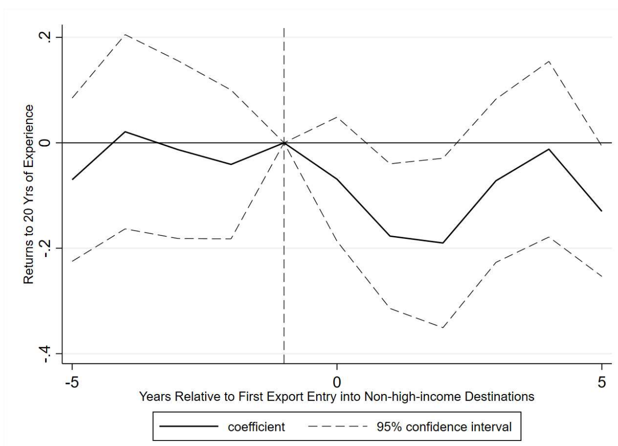
E Additional Graphs

Figure E.1: Log Hourly Wage Increase by Exporters and Non-exporters



Note: This figure presents the (employment-weighted) within-industry 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.

Figure E.2: Dynamics of Firms' First Entry Into Non-high-income Destinations



Note: The figure shows the β_τ parameters from estimating equation (4), 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, the shares of high-school graduates and cognitive workers in the workforce, firm size, and a dummy variable indicating whether the firm is exporting to a high-income destination. To estimate the β_τ parameters after entry, we require that firms remain exporting to non-high-income destinations.

F Proofs

F.1 Proof of Optimal Quantities

We would like to choose the optimal quantities $\{y_n\}$ given the export decisions $\{I_n(z)\}$:

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

We can redefine the problem as:

$$\max_{\{y_n\}} \sum_n I_n(z) \left(y_n^{\frac{\sigma-1}{\sigma}} P_n Y_n^{\frac{1}{\sigma}} - P_1 f_n \right) + \lambda \left(zh(z) - \sum_n I_n(z) \tau_n y_n \right). \tag{F.2}$$

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

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

Solving these first-order conditions leads to:

$$y_n(z) = \frac{I_n(z) P_n^{\sigma} Y_n \tau_n^{-\sigma}}{\sum_{n'=1}^{N} I_{n'}(z) P_{n'}^{\sigma} Y_{n'} \tau_{n'}^{1-\sigma}} zh(z), \tag{F.3}$$

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

$$\lambda = \frac{\sigma - 1}{\sigma} \left(\sum_{n'=1}^{N} I_{n'}(z) P_{n'}^{\sigma} Y_{n'} \tau_{n'}^{1-\sigma} \right)^{\frac{1}{\sigma}} (zh(z))^{-\frac{1}{\sigma}}. \tag{F.4}$$

F.2 Proof of Proposition 1

F.2.1 Optimal Hires and Export Choices

Because unemployment benefits $V_t = 0$ and the discount rate ρ is large enough, firms obtain a fixed portion $(1 - \beta)$ of total sales according to equation (13). Given destination $\{I_n(z)\}$, the firm solves the optimal hires,

$$\begin{aligned} \max_{v} \quad & (1-\beta)\left[(zh(z))^{\frac{\sigma-1}{\sigma}}\left(\sum_{n=1}^{N} I_n(z)P_n^{\sigma}Y_n\tau_n^{1-\sigma}\right)^{\frac{1}{\sigma}} - P_1\sum_{n} I_n(z)f_n\right] - c_vP_1v \\ \text{s.t.} \quad & h(z) = \frac{v}{V}\bar{h},\ v \geq 0 \end{aligned} \tag{F.5}$$

where $\frac{v}{V}$ is the number of workers hired by the firm in each period, and $\bar{h}$ is the average efficiency unit per worker. Because discount rate ρ is large enough, time spent on human capital accumulation i is relatively small compared with $\bar{h}$ and thus does not show up. The first-order condition of equation (F.5) is:

$$\frac{(1-\beta)(\sigma-1)}{\sigma}\left(\sum_{n=1}^{N} I_n(z)P_n^{\sigma}Y_n\tau_n^{1-\sigma}\right)^{\frac{1}{\sigma}}\left(\frac{z\bar{h}}{V}\right)^{\frac{\sigma-1}{\sigma}} v^{-\frac{1}{\sigma}} = c_vP_1$$

Solving this yields the optimal v,

$$v = \left(\frac{(1-\beta)(\sigma-1)}{\sigma}\right)^{\sigma}\left(\sum_{n=1}^{N} I_n(z)P_n^{\sigma}Y_n\tau_n^{1-\sigma}\right)\left(\frac{z\bar{h}}{V}\right)^{\sigma-1}(c_vP_1)^{-\sigma} \tag{F.6}$$

Combining this with equation (F.3), it is easy to see

$$y_n(z) = I_n(z)P_n^{\sigma}Y_n\tau_n^{-\sigma}\left(\frac{(1-\beta)(\sigma-1)}{\sigma}\right)^{\sigma}\left(\frac{z\bar{h}}{V}\right)^{\sigma}(c_vP_1)^{-\sigma} \tag{F.7}$$

If $I_n(z) = 1$, combined with $p_n = y_n^{-\frac{1}{\sigma}}P_nY_n^{\frac{1}{\sigma}}$, we obtain

$$p_n(z) = \frac{\sigma\tau_nc_vP_1V}{(\sigma-1)(1-\beta)z\bar{h}}, \tag{F.8}$$

which resembles a Melitz-Chaney-type model with labor costs $\frac{c_vP_1V}{(1-\beta)\bar{h}}$ per efficiency unit, and $\frac{\sigma}{\sigma-1}$ is the constant markup. Because workers capture a portion β of firms' revenue, workers' average wage at firm z is

$$\bar{w}_1 = \bar{w}_1(z) = \beta\bar{h}\frac{\sum_n I_n(z)p_n(z)y_n(z)}{h(z)} = \frac{\sigma\beta c_vP_1V}{(\sigma-1)(1-\beta)}, \tag{F.9}$$

which is identical across firms.

As shown in equation (F.7), 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 if $(1-\beta)p_n(z)y_n(z) \geq f_nP_1$.

F.2.2 Trade Shares in the Home Market

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

$$\begin{aligned}\Pi_d &= \frac{\bar{M}\int_{z_{\min}}^{\infty} p(z)^{1-\sigma} d\Phi(z)}{\bar{M}\int_{z_{\min}}^{\infty} p(z)^{1-\sigma} d\Phi(z) + \bar{M}^I (p^I)^{1-\sigma}} \\ &= \frac{\bar{M}\int_{z_{\min}}^{\infty} z^{\sigma-1} d\Phi(z) \left(\frac{\sigma c_v P_1 V}{(\sigma-1)(1-\beta)\bar{h}}\right)^{1-\sigma}}{\bar{M}\int_{z_{\min}}^{\infty} z^{\sigma-1} d\Phi(z) \left(\frac{\sigma c_v P_1 V}{(\sigma-1)(1-\beta)\bar{h}}\right)^{1-\sigma} + \bar{M}^I (p^I)^{1-\sigma}},\end{aligned} \tag{F.10}$$

where we use equation (F.8). Note this is a standard gravity equation with trade elasticity α, as typically used in the trade literature (reviewd by Costinot and Rodríguez-Clare 2014). And the price index in the home country,

$$P_1 = \left(\bar{M}\int_{z^*_{\min}}^{\infty} z^{\sigma-1} d\Phi(z) \left(\frac{\sigma c_v P_1 V}{(\sigma-1)(1-\beta)\bar{h}}\right)^{1-\sigma} + \bar{M}^I (p^I)^{1-\sigma}\right)^{\frac{1}{1-\sigma}}. \tag{F.11}$$

F.2.3 Gains from Trade

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

$$X_1 = \frac{\bar{w}_1}{\beta P_1} = (\Pi_d)^{-\frac{1}{\sigma-1}} \bar{h} \left(\bar{M}\int_{z^*_{\min}}^{\infty} z^{\sigma-1} d\Phi(z)\right)^{\frac{1}{\sigma-1}} \tag{F.12}$$

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

$$GT = \underbrace{\Pi_d^{-\frac{1}{\sigma-1}}}_{\text{changes in real income per efficiency labor}} \times \underbrace{\frac{\bar{h}}{\bar{h}^{auc}}}_{\text{changes in average efficiency labor per employee}}. \tag{F.13}$$

This completes the proof.

G 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 experiment 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 revenue and the increment in human capital per time spent affect experience effects. This is motivated by our estimated effects in Table 3 that capture the short-run effects.[45] 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.

H 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 2019). In particular, we assume for a worker of age t at firm z, the human capital growth is exogenously given by:

$$\phi_t^E(z) = \mu z^{\gamma_1} \left(\phi^O(z)\right)^{\gamma_2} \exp(-\rho_h t). \tag{H.1}$$

Compared with our baseline model, we now assume: 1) there is no time needed for human capital accumulation, and this implies $i_t = 0$ in our baseline results; 2) to generate reduction in learning speed in later ages, we introduce an additional parameter $\rho_h > 0$.

We recalibrate our model parameters to the targeted moments with this alternative assumption on human capital growth.[46] We find that the model with this learning-by-doing assumption is unable to generate the (untargeted) negative change in experience returns from entry to non-high-income destinations, as shown in Table 8. Even though non-high-income destinations on average have higher GDP per capita than Brazil, our baseline model is able to generate the negative experience returns from entry to non-high-income destinations because export revenues also raise the opportunity cost of human capital investment

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

[46] As we introduced a new parameter ρ_h, we also introduce a new targeted moment—the returns to the first 5 years of workers' experience.

Table H.1: Changes in Returns to 20 Yrs of Experience due to Export Entry (Learning-by-doing)

	Data	Model	Model-based Decomposition		
			Human Capital	Piece Rate	Investment
Entry into high-income destinations	0.23	0.21	0.195 (93%)	0.015 (7%)	0 (0%)
Entry into non-high-income destinations	-0.02	0.01	0.01 (86%)	0.00 (14%)	0 (0%)

Notes: The data on experience returns with regard to export entry is the average of reduced-form evidence in Table 3 and D.5. The percentage in brackets refer to the contribution of each channel to the overall model-generated change.

and thus reduce human capital investment. However, this change in opportunity costs of human capital accumulation does not show up in the model with learning-by-doing.