Exporting, Wage Profiles, and Human Capital: Evidence from Brazil

Ma, Xiao and Muendler, Marc-Andreas and Nakab, Alejandro

Peking University, UC San Diego, CESifo and NBER, Universidad Torcuato Di Tella

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Xiao Ma
Peking University

Marc-Andreas Muendler
UC San Diego, CESifo and NBER

Alejandro Nakab
Universidad Torcuato Di Tella

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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 firms' export market entry, worker-firm wage bargaining, and workers' human capital accumulation to interpret the data and perform counterfactual experiments. We find that human capital growth can explain roughly one-half of the 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 trade partners are predominantly low-income destinations.

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

*Email: xiaoma@phbs.pku.edu.cn, muendler@ucsd.edu, and anakab@utdt.edu. We thank Titan Alon, Haichao Fan, Gordon Hanson, Ruixue Jia, David Lagakos, Tommaso Porzio, Valerie Ramey, Natalia Ramondo, Jeffrey Smith, Felix Tintelnot, and seminar participants at the Annual Meeting of China Trade Research Group, UC San Diego, and the PILLARS conference on Education, Skills, and Worker Retraining. Xiao Ma also acknowledges the support from the National Natural Science Foundation of China (72203012). Any errors are our own.

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), but 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. However, despite much attention to static differences in wages between exporters and non-exporters (Bernard and Jensen 1995) and to firm-level differences in lifecycle wage growth in recent studies (Herkenhoff et al. 2018, Gregory 2019, Jarosch et al. 2021), 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 information on job characteristics. To construct experience-wage profiles, we measure workers' potential experience in the labor market as years elapsed after schooling and then estimate how one extra year of experience within a job (worker-firm match) affects wage growth for workers in different lifecycle stages. 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 at the end of the working life,[2] and hence old workers' wage growth allows us to isolate time effects.

We document three facts. First, after staying in a job for 20 years from the beginning of the career, a typical worker's 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 most of the differences in experience-wage profiles between exporters and non-exporters, hint-

[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] 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).

ing that exporters essentially provide higher returns to experience. Third, after controlling for productivity proxies, labor composition, and firm fixed effects, returns to experience are 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-score matching approach or exploit massive currency devaluations to lessen the endogeneity concern of export decisions.

We show our empirical results are robust to using the subsample of workers that are observed in the data since a young age and for whom we can construct experience based on the observed work history. Because of possible breaks in the observed employment records (due to reasons such as unemployment), which resolve the collinearity between experience and time, we do not need to impose the HLT assumption in estimation. We still find that previous experience at exporters (especially those selling to high-income markets) is more valuable than experience at non-exporters, and that these experience effects are largely portable after workers switch firms. The estimated experience effects are of similar magnitude to our previous findings. We also show similar results for 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 worker-firm rent sharing, as suggested by a large literature quantitatively studying the earnings dynamics (e.g., Rubinstein and Weiss 2006, Barlevy 2008, Yamaguchi 2010, Burdett et al. 2011, Bagger et al. 2014, Gregory 2019). The second contribution of this paper is to develop and quantify a model with firms' export market entry, worker-firm wage bargaining, and human capital accumulation to interpret the data and conduct experiments.

Our model builds on Cahuc et al. (2006), in which firms meet workers by random search. Workers and firms negotiate the contractual piece rate (portion of revenues accruing to the worker) when workers are hired, and they can renegotiate the piece rate when workers receive attractive offers from outside firms. Workers divide their time between working and human capital accumulation. Guided by our evidence, we embed two novel features into the model. First, the increment in human capital per time spent increases with firm productivity and the sales-weighted average knowledge stock in firms' markets.[3] Thus, staying in highly productive firms (which tend to select into exporting) and being exposed to destinations with affluent knowledge can produce faster human capital growth. Second, we consider destina-

[3] Modeling 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.

tions to be heterogeneous in their knowledge stocks, and therefore different combinations of destinations imply vastly different learning opportunities for workers.

In the model, workers' within-job wage profiles reflect human capital growth, changes in time allocated to working, and wage renegotiations. To understand their relative contributions, we calibrate our model to the Brazilian manufacturing sector and target relevant moments to discipline the strength of wage bargaining 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 50% 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 apply our calibrated model to understand the quantitative effects of trade openness. We find that the gain in real income from autarky to the calibrated economy is 7.78%, and a large contributor is human capital formation: Workers enjoy a 3.98% increase in average efficiency labor due to trade openness. We then perform a decomposition of the trade-induced increase in workers' human capital, and consistent with our empirical evidence, this increase is mostly driven by increased knowledge after firms' entry into high-income destinations. To understand the impact of further trade liberalization, we lower trade costs from Brazil to specific export destinations in our calibrated model. We find that the gains in real income depend on destinations' knowledge stocks and are not necessarily positive. Lowering trade costs to high-income destinations by 10% would increase Brazil's real income by 1.78%, largely due to a 1.38% increase in workers' average human capital. Surprisingly, lowering trade costs to non-high-income destinations by 10% would reduce Brazil's real income by 0.13%, mainly driven by a 0.74% decline in workers' average human capital.

This paper relates to several strands of the literature. We directly contribute to the literature on learning by exporting. Recent papers show that through acquiring new knowledge from exporting, firms can improve their technical efficiency (Aw et al. 2011, De Loecker 2013, Atkin et al. 2017) or understanding of export demand (Albornoz et al. 2012, Morales et al. 2019). Fewer studies explore how workers may also acquire knowledge from trade, including how firms' import and export choices are related to employees' previous experience (Mion and Opromolla 2014, Muendler and Rauch 2018, Labanca et al. 2021), managerial practices and networks (Bisztray et al. 2018, Bloom et al. 2018) or firms' organization (Caliendo and Rossi-Hansberg 2012, Caliendo et al. 2020). Artopoulos et al. (2013) provide case studies in

Argentina, showing that export pioneers learn to adopt new practices for foreign 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 larger exposure to advanced export destinations.

Our paper also makes 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), industry composition (Dix-Carneiro 2014), and match quality (Menzio et al. 2016).[4] There are few studies exploring the role of export participation in lifetime wage growth. Mion et al. (2020) find higher wage profiles in internationally active firms than in domestic firms. Differing from their paper, our paper also explores the relationship between export destinations and workers' wage profiles, and we develop a structural model to *quantify* the aggregate implication. By emphasizing how export destinations impact wage growth through human capital formation, our paper complements a broad literature focusing on the determinants of on-the-job human capital accumulation (e.g., Manuelli and Seshadri 2014, De la Croix et al. 2018, Doepke and Gaetani 2020). Moreover, much empirical work finds wage differences between exporters and non-exporters but abstracts from experience returns (e.g., Bernard and Jensen 1995).[5] We show that the exporter wage premium increases with workers' experience, which may partly reflect workers' faster human capital growth at exporters.

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 bargaining 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 modeling 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 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

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

[5] 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.

is particularly due to knowledge spillovers from foreign countries. Recent theoretical and quantitative 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), as reviewed by Lind and Ramondo (2019). This literature typically finds that trade speeds up productivity growth. For example, in a model calibrated to cross-country data, Buera and Oberfield (2020) find that the gains from trade more than double when they introduce diffusion of ideas from sellers in the domestic market.[6] In contrast with these papers, our paper highlights that workers' human capital accumulation may also reflect trade-induced knowledge flows. Our quantitative analysis suggests that the gains from trade almost double when we introduce workers' human capital formation with exposure to export destinations' knowledge levels.

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 bargaining, 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 present a set of stylized facts on how export activity affects experience-wage profiles in Brazil. We document that experience-wage profiles are steeper at exporters than non-exporters. We then show that steeper experience-wage profiles at exporters reflect both selection of more capable firms into exporting and the effects of exporting to more advanced destinations. We now start our analysis by first describing the data.

[6]Considering knowledge diffusion from the sellers in the domestic market, Alvarez et al. (2013) find that the GDP gain of costless trade relative to autarky is several times larger when knowledge diffusion is considered than without knowledge diffusion. Considering technology diffusion from incumbents to entrants and endogenous firm entry/exits, Sampson (2016) finds that the gains from faster technology diffusion due to trade openness are around two times of the standard static gains from trade according to Arkolakis et al. (2012). Accounting for incumbents' technology adoption decisions, Perla et al. (2015) find only a slight change in the gains from trade, because in their model, more technology adoption after trade openness is largely offset by increases in technology adoption costs.

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 for 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 B.1 describes the Brazilian economy and export patterns during our sample period.

We rely on the RAIS database between 1994–2010. It provides a complete depiction of 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).[7] 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 B.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.[8] 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 C.

We use unique 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

[7]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.

[8]This restriction on male workers follows Lagakos et al. (2018), as large changes in female labor participation rates over time may imply strong selection efforts of female workers. 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 was quite stable, changing from 81% to 77% during the same period. 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.
Panel A: workers' characteristics:				
age	31.96	9.72	32.80	9.39
schooling	8.06	3.46	8.94	3.78
log(hourly wage), Brazilian Real$	0.36	0.67	0.86	0.83
cognitive occupations (1 if yes)	0.19	0.39	0.24	0.43
production worker (1 if yes)	0.74	0.44	0.70	0.46
share of workers in the sample	0.47	–	0.53	–
Panel B: firms' characteristics:				
log(employment)	3.18	0.79	4.52	1.37
log(exports per worker), U.S.$	–	–	7.32	2.16
number of export destinations	–	–	5.56	8.45
ratio of # high-income to # total export destinations	–	–	0.34	0.38

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.

contains destinations and 8-digit products each firm exports in each year. For 1997–2000, the data also provides information on export quantity and value (U.S.$), covering 90% of Brazilian officially reported total exports between 1997–2000.[9] Appendix Figure A.1 shows that between 1997–2000, each country's (product's) share of Brazilian annual exports from our customs data matches the official data from the Brazilian Ministry of Economy well.

Panel A of Table 1 describes characterizations of the RAIS database, based on worker-firm-year observations. In our sample, 53% of worker-firm-year observations are at exporters, and thus export activity is nontrivial in our sample. On average, relative to workers at non-exporters, workers at exporters are slightly older and more educated, and earn higher hourly wages. Workers at exporters also tend to work in cognitive occupations (professionals, technicians, and other white-collar jobs) or as nonproduction workers.[10] Moreover, according to

[9]The total exports reported by our customs data account for 91%, 91%, 88%, and 87% of officially reported total exports in 1997, 1998, 1999, and 2000, respectively.

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

firms' characteristics in Panel B of Table 1, exporters are much larger in terms of employment than non-exporters. These pieces of evidence on workers and firms are consistent with the exporter premium typically found in the literature (e.g., Bernard et al. 2003, Verhoogen 2008). Finally, in our empirical analysis, we will study how returns to experience depend on firms' export destinations. On average, an exporter exports to 5.6 destinations, and among them 34% of destinations are high-income countries, where countries are classified as high-income countries according to the World Bank classification in 2000.[11]

In Appendix C.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.[12] 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

2.2.1 Constructing Wage Profiles

We consider a job as a worker-firm 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:

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

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. $\Delta \log(w_{i,t})$ denotes within-job wage growth, which is

[11]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. Our empirical results are robust if we consider changes in Brazil's relative income levels in the world, as shown in Section 2.3.3.

[12]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.

log hourly wage growth from $t-1$ to t for individual i within the same firm.[13]

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 between age minus 18 and age minus 6 and schooling, min{age-18,age-6-schooling}. $D^x_{i,t}$ 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^x_s measures returns to one extra year of experience for workers in experience bin x, and thus we allow experience returns to nonparametrically differ across lifecycle stages (measured by experience bin x), because experience returns change as workers grow old. $\gamma_{s,t}$ 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 $\sum_x D^x_{i,t} = 1$ is perfectly correlated with the constant $(\gamma_{s,t} - \gamma_{s,t-1})$ 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). 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.[14] 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 $\phi^{31-35}_s + \phi^{36-40}_s = 0$. Appendix D.1 provides details on the approach.

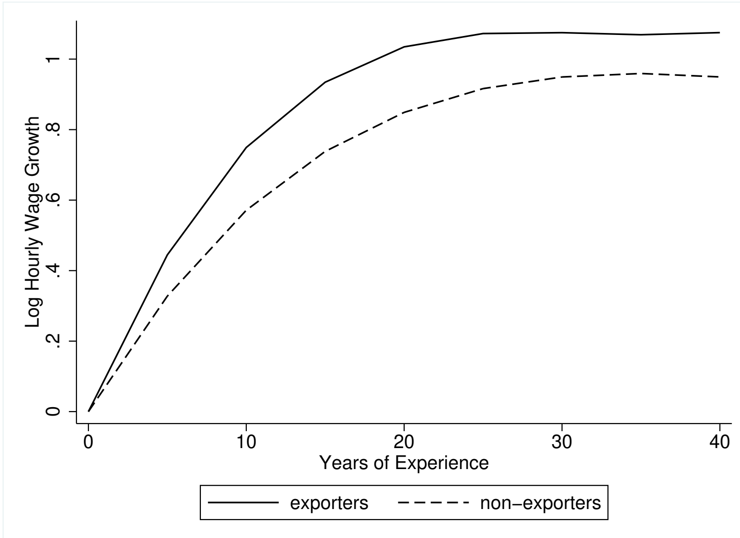
2.2.2 Wage Profiles for Workers at Exporters and Non-exporters

We apply equation (1) to estimate experience-wage profiles using our sample. As we focus on the effects of firms' export activity on wage profiles, we relegate the discussion of the role of industry composition to Appendix E.1 and show that it does not drive the difference in

[13] As the time effects $\gamma_{s,t} - \gamma_{s,t-1}$ 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.

[14] 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 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.

returns to experience between exporters and non-exporters in our sample. We always control for industry effects when comparing wage profiles between exporters and non-exporters.[15] 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 her 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.

Appendix Figure A.2 shows that the relative 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 rate shifts exporters' and non-exporters' wage profiles by the same amount and thus does not affect the relative differences. Because depreciation rates can matter for the aggregate amount of human capital, we will calibrate and discuss the depreciation rate of human capital in the quantitative analysis.

[15]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.

2.3 Firm-level Wage Profiles and Export Destinations

2.3.1 Constructing Firm-level Wage Profiles

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,

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

where ω refers to a firm. The returns to one-year experience $\phi^x_{\omega,t}$ are now firm-specific and also time-variant to allow for 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. 2019). 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 final 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 $(\gamma_{\omega,t} - \gamma_{\omega,t-1})$.[16] Hence, we can construct an estimate for annual returns to experience in experience bin x by

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

$\frac{\sum_{i \in \omega} D^x_{i,t} \Delta \log(w_{i,t})}{\sum_{i \in \omega} D^x_{i,t}}$ represents the average individual-level wage growth between $t-1$ and t, for workers at firm ω in both periods and in experience bin $x \in X = \{1\text{–}5,...,36\text{–}40\}$. 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 revenues after exporting, this effect will not show up in the estimated experience returns of workers in firm ω. However, if the wage growth is relatively higher for young workers than old workers, this relative difference will be interpreted as returns to experience.

[16] If only one term of $\frac{\sum_{i \in \omega} D^{31-35}_{i,t} \Delta \log(w_{i,t})}{\sum_{i \in \omega} D^{31-35}_{i,t}}$ and $\frac{\sum_{i \in \omega} D^{36-40}_{i,t} \Delta \log(w_{i,t})}{\sum_{i \in \omega} D^{36-40}_{i,t}}$ exists, we use the existing one to construct firm-specific wage trends.

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***	0.021	-0.015	-0.051	-0.071	-0.037
	(0.013)	(0.030)	(0.035)	(0.073)	(0.127)	(0.126)
Exporter × ratio of # high-income to # total dests			0.134***	0.239**		
			(0.052)	(0.110)		
Exporter × share of exports to high-income dests					0.183*	
					(0.104)	
Exporter × log(avg GDPPC of dests)						0.128**
						(0.062)
Exporter × log(# total dests)			-0.007	0.038	0.029	0.029
			(0.020)	(0.053)	(0.060)	(0.060)
Exporter × log(avg exports per employee)					0.007	0.006
					(0.022)	(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	344,658	344,658	344,658	77,847	77,847	77,847
R-squared	0.007	0.319	0.319	0.489	0.489	0.489

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: 1) average years of schooling; 2) the share of workers with high-school degrees; 3) the share of cognitive workers; 4) the share of production workers; 5) average workers' age; 6) firm employment size; and 7) firm employment percentiles (divided into 10 bins) within each industry-year bin. Robust standard errors are in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

2.3.2 Linking Firm-level Wage Profiles with Firm Characteristics.

In Table 2, we regress firm-year-level returns to 20 years of experience on firm characteristics. The dependent variable is $5 \times \sum_{x\in\{1-5,\ldots,16-20\}} \hat{\phi}^x_{\omega,t}$, 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 little returns to experience after 20 years of experience (Figure 1).[17]

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

[17] We can compute returns to 20 years of experience for 36% of firm-year observations, covering 80% of total manufacturing employment in the sample.

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.

Exporters' premium in experience returns may reflect exporters' advantages in labor composition or technology levels (Islam et al. 2018). Thus, in Column (2), we control for workers' education levels (average years of schooling and the share of workers with high-school degrees),[18] occupation structure (the shares of production and cognitive workers), and workers' average age. Because we do not have firm-level production data, we control for firm employment size, which is associated with firm productivity (Hopenhayn 1992), and we also control for firms' employment percentiles (divided into 10 bins) to allow for nonlinear impacts of employment. Finally, we control for firm fixed effects, capturing time-invariant unobserved factors.[19] After including these controls, the resulting exporters' premium in experience returns declines (relative to Column (1)) and nearly vanishes, suggesting that higher returns to experience at exporters reflect selection of better firms into exporting. Appendix Table A.1 reports how each control variable affects experience returns and shows that experience returns are higher if there are more educated, cognitive, or nonproduction workers in the workforce, consistent with Islam et al. (2018). We also find that solely controlling for firm employment can lead to 57% of the overall decline in exporters' premium of experience returns after including all control variables, indicating that more productive firms provide higher returns to experience and are more likely to select into exporting.[20]

We then 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 also control for the number of export destinations, as the scope of destinations may matter. We find that firms which export more to high-income destinations experience steeper wage profiles. The coefficient suggests that other things being constant, a firm exporting solely to high-income

[18]We control for the share of workers with high-school degrees to allow for nonlinear impacts of schooling (Katz and Murphy 1992). In our sample, the share of workers with high-school degrees is 32%, while the share of workers with college degrees is only 4%. We find that controlling for the share of workers with college degrees leads to very similar results.

[19]After controlling for firm fixed effects, the estimation of the impact of export activity on wage profiles relies on within-firm changes in export activity over time. In our sample, changes in export activity are non-trivial: Conditional on the current year's export status, 3% of non-exporters would start exporting in the next year, and 13% of exporters would stop exporting in the next year.

[20]We find that after including firm fixed effects, the coefficients on most of the control variables become insignificant, indicating that firms which provide higher returns to experience essentially have a better workforce and are more productive.

countries has a 13-percentage-point gain of returns to 20 years of experience compared with a firm exporting solely to middle- and low-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, 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 revenues 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.[21] We find that exporting to destinations with higher income significantly increases returns to experience.

2.3.3 Robustness Checks

Classification of High-income Destinations. Considering that Brazil's fast economic growth in the 1990s and 2000s may change its relative position with regard to export destinations, we now use each year's country-level GDP per capita. In Appendix Table A.2, we construct exposure to high-income destinations using the ratio of the number of export destinations with higher-than-Brazil GDP per capita in the corresponding year to the total number of destinations, or export-weighted GDP per capita across destinations (relative to Brazil's GDP per capita) in the corresponding year.[22] We find quantitatively similar impacts of export activity on experience returns compared with our baseline results in Table 2.

Discussion of the HLT Assumption. We assumed the final 10 years of no experience effects to construct firm-specific wage trends. Appendix Table A.3 shows that the coefficients are similar to those in Table 2 if we assume the final 5 years with no experience returns.

Another issue is that young and senior workers may be different in many aspects (e.g.,

[21] 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. Appendix Table A.2 shows that the empirical findings are similar when we use each year's country-level GDP per capita to construct export-weighted GDP per capita across destinations.

[22] In unreported results, we also experimented with many other thresholds on yearly GDP per capita to define high-income destinations (for example, a destination is defined to be high-income if its GDP per capita exceeds Brazil's by 100% in the corresponding year), and found similar empirical results as in Table 2. These results are available upon request.

education levels), and thus senior workers' wage growth may not represent young workers' wage growth in the absence of returns to experience. To rule out this issue, we directly regress the average yearly wage growth of workers in each experience bin on the exporter dummy and exposure to high-income destinations, controlling for the corresponding workers' characteristics (education, occupation, and age) and thus allowing for different characteristics of young and senior workers to affect their respective wage growth. This approach echoes recent papers which infer the strength of human capital accumulation directly through wage growth differentials across individuals (e.g., Herkenhoff et al. 2018, Jarosch et al. 2021).

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

Workers' and Firms' Past Experience at Exporters. Recent research suggests that past experience of managers and coworkers at exporters facilitates exporting (Mion and Opromolla 2014, Muendler and Rauch 2018). In Appendix Table A.5, 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 experienced managers and coworkers.

Role of Tenure. Our estimates on experience returns may be confounded by tenure effects, as low tenure at the current firm may also lead to fast wage growth (Topel 1991, Dustmann and Meghir 2005). In Appendix A.6, we control for workers' average tenure and the difference in average tenure between young and senior workers within the firm, and we find that the coefficients of interest barely change compared with our baseline results in Table 2.

Role of Product Quality. One possible explanation of destination-specific experience returns is that exporting to high-income destinations may require high-quality goods, which may lead to changes in workers' skills. Whereas it is difficult to directly observe export quality, one observation is that product quality is positively correlated with export prices (Schott 2004, Manova and Zhang 2012). In Appendix Table A.7, we construct firm-year-level export prices in the period of 1997–2000[23] and show that controlling for average export

[23]Because unit prices are not directly comparable across products, we first compute firms' unit prices of

prices does not affect our estimated impact of high-income destinations on wage profiles, indicating that quality upgrading may not be the driver for this destination-specific impact.

Female Employees. In our baseline results, we focus on male employees to avoid selection issues regarding female labor participation. As shown in Appendix Table A.8, in line with our findings for male employees, we find quantitatively similar impacts of high-income destinations on experience returns for female employees.

Industry Heterogeneity in Destination-specific Returns. We now explore how the impact of export destinations on experience returns varies across industries. In Appendix Table A.8, we divide industries into differentiated and non-differentiated industries.[24] We show that workers in differentiated industries enjoy large and significant increases in returns to experience due to high-income destinations, whereas workers in non-differentiated industries have insignificant and small changes in returns due to destinations. This indicates that our finding may be partly driven by workers' human capital accumulation, as differentiated products tend to be associated with larger scope of workers' learning opportunities.[25]

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

Heterogeneity in Destination-specific Returns across Firms. In Appendix Table A.9, we explore how the impact of export destinations varies with firm characteristics by incorporating the interaction between firm characteristics and exposure to high-income destinations into the regression of Column (3) in Table 2. We find that the impact of export destinations on experience returns does not vary significantly with the workforce's education levels, occupation structure, and average age, as well as the firm's employment size.[26]

products relative to average unit prices of exports to Argentina (which is of similar development levels to Brazil) for each 8-digit product and year. We then use export volume as weights to compute a weighted average unit price of exports for each firm and year. The results are quantitatively similar if we use the U.S. as the benchmark country to construct relative unit prices of products.

[24]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).

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

[26]Mion et al. (2020) find higher wage profiles for managers (a subset of nonproduction workers) in internationally active firms in Portugal. In our sample, we do not find our estimated impact of export destinations on wage profiles changes significantly with the share of managers in the firm's workforce, as shown in Column

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

2.4.1 Event Study

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

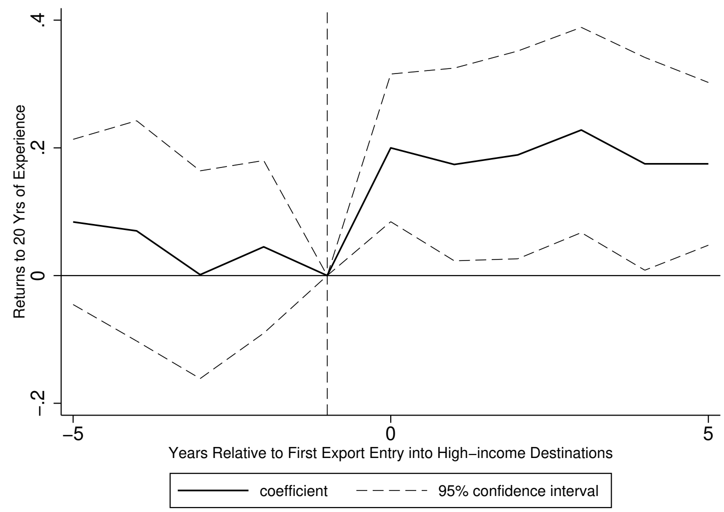
$$y_{\omega,t} = \sum_{\tau=-4}^{\tau=-2} \beta_\tau 1\{high\_inc\}_{\omega,t^*+\tau} + \sum_{\tau=0}^{\tau=4} \beta_\tau 1\{high\_inc\}_{\omega,t^*+\tau} + \beta_{pre} \sum_{\tau\leq -5} 1\{high\_inc\}_{\omega,t^*+\tau} + \beta_{post} \sum_{\tau\geq 5} 1\{high\_inc\}_{\omega,t^*+\tau} + \mathbf{X}_{\omega,t}^{'}\mathbf{b}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

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 all the control variables in Table 2, and a dummy variable indicating whether the firm is exporting to a non-high-income destination.

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

(6) of Appendix Table A.9, where managers include senior managers and supervisors according to Muendler et al. (2004). In Appendix Table A.8, we construct firm-year-level experience returns separately for production and nonproduction workers. We do not find the impact of exposure to high-income destinations on experience returns is significantly different between production and nonproduction workers. However, due to the small portion of nonproduction workers within firms (around 30%), the impact of export destinations on nonproduction workers' wage profiles is noisily estimated and insignificant. As managers only make up a very small portion (4%) of a firm's workforce in our sample, we do not construct experience returns separately for managers.

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, and a dummy variable indicating whether the firm is exporting to a non-high-income destination. The other controls are: 1) average years of schooling; 2) the share of workers with high-school degrees; 3) the share of cognitive workers; 4) the share of production workers; 5) average workers' age; 6) firm employment size; and 7) firm employment percentiles (divided into 10 bins) within each industry-year bin. To estimate the β_τ parameters after entry, we require that firms remain exporting to high-income destinations.

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.[27] 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 A.3 estimates the β_τ parameters for the firm's first export entry into non-high-income destinations at time $t = t^*$ ($\tau = 0$). We find no significantly positive changes in returns to experience after entry to non-high-income destinations.[28]

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

[28]Appendix Figure A.4 estimates the β_τ parameters for the firm's first export entry regardless of destinations, and the estimated coefficients are between the effect of exporting to high-income destinations and that of exporting to non-high-income destinations. Although the impact of firms' first export entry regardless of destinations tends to be small, in the data, conditional on being an exporter, larger firms export more to richer destinations: The share of exporters that export to high-income destinations is 15 percentage points

Figure 2 also shows that most of the gains in returns to experience materialize immediately after entry to high-income destinations ($\beta_0 = 0.20$) and slightly increase in three years after export entry ($\beta_3 = 0.23$). This pattern is consistent with De Loecker (2007) who finds that the immediate firm productivity gain after export entry is large, and that the gain only slightly changes after export entry. Appendix Figure A.5 reports the impact of entry into high-income destinations on experience returns for workers in different lifecycle stages. The increase in the impact after years of export entry mainly occurs for the youngest workers (with 1–5 years of experience), indicating that the youngest workers may enjoy slightly larger benefits over time after export entry, though the increase is relatively mild compared with the immediate response. This immediate response will be consistent with the mechanisms exploited (worker-firm rent sharing and human capital) in our model, as exporting to high-income destinations immediately changes the scope of worker-firm rent sharing and the human capital increment per time spent.

2.4.2 Propensity-score Matching Estimator

To control for self-selection into exporting, we apply the propensity-score matching estimator (Heckman et al. 1997, see Appendix D.2 for details).[29] The key of this matching estimator is choosing an appropriate set of non-exporters based on export probability as the control group for exporters. The assumption of identification is that conditional on export probability, firms' performance (in the absence of exporting) is independent of the current export status, and thus we can use the performance of the control group to proxy the counterfactual scenario of no export entry for exporters. This assumption is more likely to hold when we estimate the export probability based on a larger set of firms' observables.

Thus, we first estimate each firm's probability to start to export to high-income destinations based on a Probit model, controlling for a wide range of pre-exporting (previous year) firm characteristics, including returns to experience, workers' education levels, workers' occupation structure, workers' average age, firm size, and export status to non-high-income destinations, as well as industry and year fixed effects. We then choose the matched control group based on the method of the nearest neighbor,[30] which selects a non-exporting firm

higher for firms with above-median employment levels than firms with below-median employment levels. This pattern suggests that the aggregate impact tends to reflect the effect of high-income destinations.

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

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

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

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

which has an export probability closest to that of the export entrant. Appendix Table A.10 reports the t-tests showing that all the observables (used in constructing the export probability) are similar between the chosen control group and the export entrants, and thus our matching estimator satisfies the balancing hypothesis (see Rosenbaum and Rubin (1984)).

Panel (a) of Table 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 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.

Appendix Table A.11 reports future effects for new exporters that stop exporting in future periods. Increases in returns to experience become much smaller after firms stop exporting, and the statistical significance vanishes. This suggests that large increases in returns to experience are associated with continuing exporting to high-income destinations. Finally, Appendix Table A.12 replicates Table 3 for entry to non-high-income destinations, and we find no statistically significant changes in returns to experience after export entry.

2.4.3 Brazilian Currency Crisis

Recent studies exploit periods of massive currency devaluations as quasi-experiments to study the causal impact of export entry on firm performance (e.g., Verhoogen 2008, Macis and Schivardi 2016). In Appendix E.2, we study a Brazilian currency crisis in 1999, when the Brazilian Real per U.S. dollar experienced a 60% devaluation within two months. We show that the currency devaluation encouraged more export entry. We also find significantly higher returns to experience for firms that exported to high-income destinations following this currency crisis, after controlling for pre-exporting export patterns and firm fixed effects.

2.5 Worker-level Results

In Appendix E.3, we construct a panel of young workers that first appear in RAIS within 5 years after finishing schooling. 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, firm fixed effects, and year 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 continues to work for 20 years at exporters, her wage growth is 15 percentage points higher than working at non-exporters, which is in line with the results in Section 2.2. Second, after controlling for firm-specific previous experience, we find that if a worker starts to work in a new firm after 20 years of experience at exporters, she enjoys a 11% higher wage than previously working at non-exporters for 20 years. This result suggests that the experience effects are largely portable after switching firms. 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 7% higher wage than working at exporters that only export to non-high-income destinations.

We further analyze a sample of displaced workers due to closure of large firms. These displaced workers' firm seniority is exogenously set to zero, and their returns to previous experience most likely reflect learning, providing an ideal scenario for studying experience effects (e.g., Dustmann and Meghir 2005, Arellano-Bover and Saltiel 2021). Using this sample, 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 a 12% higher post-displacement wage than previously 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.

While one can never establish direct causal links beyond doubt with nonexperimental data, the similarity between worker-level and firm-level results and across different estimation methods bolsters our confidence that steeper experience-wage profiles at exporters (than non-exporters) partly reflect the effects of entering more advanced export destinations.

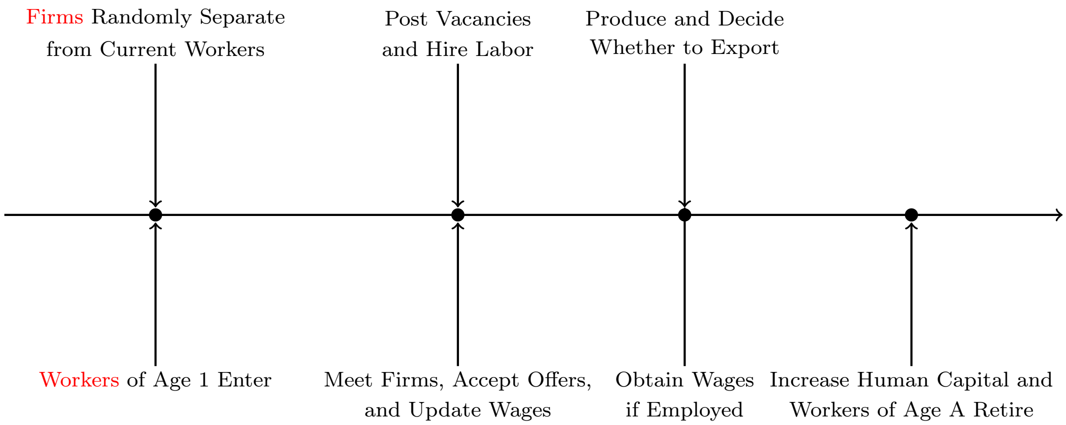
3 Model

To understand the factors behind the impact of export activity on wage profiles and its aggregate implications, we proceed to develop a quantitative model. Motivated by our evidence and the literature quantitatively studying the earnings dynamics, we consider that wage profiles reflect human capital formation as well as changes in worker-firm rent sharing.

In the model, workers meet jobs by random search. Workers and firms negotiate the contractual piece rate, which stipulates the portion of revenues accruing to the worker. The piece rate is worker-firm-specific and determined through the processes of bargaining, which happens when an unemployed worker accepts a job or when an employed worker is poached by an outside firm with an attractive offer. Workers divide their time between working and human capital accumulation. Motivated by our empirical findings, we consider the increment in human capital per time spent may depend on destination markets' knowledge. For tractability, we restrict our attention to one single dimension of general human capital.[31] On the production side, firms have heterogeneous productivity levels and face iceberg and fixed export costs (Melitz 2003). We consider that both export revenues and the impact

[31] The firm-specific components of human capital have been found to be much less important for wage growth than the general human capital (Altonji and Shakotko 1987, Lazear 2009, Kambourov and Manovskii 2009), and our worker-level evidence also suggests that most of the human capital gained at exporters is portable when workers switch firms. The focus on general human capital is also typical in the quantitative literature on earnings dynamics (e.g., Bagger et al. 2014, Manuelli and Seshadri 2014).

Figure 3: Timing of Events in Each Period



of export activity on workers' human capital accumulation are taken into consideration of making export decisions.

We focus on a steady state in which aggregate variables are constant. We index workers by i and firms by ω. The timing of events in each period is provided in Figure 3.

3.1 Model Setup

3.1.1 Workers

Age Structure. Overlapping generations of workers participate in the labor market from age $a = 1, 2, .., A$. Workers of age A retire at the end of each period and are replaced by new entrants of age 1. The population of each generation is normalized to 1, and thus the total population is A. The introduction of workers' age structure enables our model to generate wage profiles that are comparable to our empirically constructed wage profiles. Moreover, because returns of human capital accumulation decline with age and most of senior workers already enjoy good bargaining positions, our model is also able to numerically generate little experience effects in the final working years, which is a key assumption in our HLT approach.

Utility. Workers have linear utility for consumption of a nontradable final good, and they discount the future at rate ρ. The final good is composed of differentiated varieties sourced from domestic or foreign origins, as described below.

Labor Market Search. Labor markets are subject to search frictions as illustrated by Figure 3. At the beginning of each period, existing jobs are terminated at an exogenous rate κ. New entrants of age 1 begin their career as unemployed. Unemployed and employed people then match job vacancies randomly at rates λ_U and λ_E respectively. Let U be the total amount of unemployed people before job search happens, and $0 \leq \eta < 1$ 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: $\lambda_U = \chi\left(\frac{V}{U+\eta(A-U)}\right)$ and $\lambda_E = \eta\lambda_U$, where $\frac{V}{U+\eta(A-U)}$ is the ratio of the amount of all firms' vacancies to total search efforts. The function $\chi(\cdot)$ governs the matching process.

When an unemployed worker meets a job vacancy, we consider she will always accept the job, by assuming that unemployment is equivalent to employment in the least productive firm. This assumption resolves the complication of allowing for heterogeneous reservation wages for workers of different human capital levels and ages, as similarly used in Bagger et al. (2014). Unemployment lasts if the unemployed person does not meet a vacancy. When an employed worker meets a job vacancy, the employed worker may move to the poaching firm if the poaching offer is more attractive than the current job, as described in Section 3.2.1.

Wage. In firm ω, wages vary across workers. For a worker i of age a,[32] the wage is determined by $w_i^a(\omega) = r_i(\omega)\tilde{z}(\omega)(h_i^a - s^a(h_i^a, \omega))$, where $\tilde{z}(\omega)$ is firm ω's revenue per unit of efficiency labor in the current period, h_i^a is worker i's human capital (total units of efficiency labor), and $s^a(h_i^a, \omega)$ is the time (in terms of units of labor) spent on human capital accumulation, as derived below in Section 3.2.3. Following Bagger et al. (2014), we consider that the worker and the firm negotiate the contractual piece rate $r_i(\omega)$, where $0 \leq r_i(\omega) \leq 1$ can be viewed as the proportion of revenues (generated by worker i) accruing to worker i and thus governs the rule regarding rent sharing between worker i and firm ω. $r_i(\omega)$ is worker-firm-specific and is determined by the history of bargaining processes between worker i and firm ω over the job surplus, as described below in Section 3.2.1.

Human Capital Accumulation. New entrants of age 1 are endowed with human capital normalized to $h_i^1 = 1$. Employed workers may accumulate human capital on the job. We assume that a worker's human capital evolves as (from age a to age $a+1$):

$$h_i^{a+1} = (1-\delta_h)h_i^a + \phi^E(\omega)s^a(h_i^a, \omega)^\alpha. \tag{5}$$

Here δ_h is the depreciation rate. $\phi^E(\omega)$ captures the increment in human capital per unit of time spent on building skills, and $0 < \alpha < 1$ captures the degree of diminishing marginal

[32] In principle, age a is a characteristic of worker i and can be suppressed. We explicitly express age a because it facilitates the characterization of a worker's value function, which depends on the amount of worker's human capital, age, and the employer, as described in Section 3.2.2.

benefits with regard to time $s^a(h_i^a, \omega)$. 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:

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

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 $z(\omega)$ to proxy the stock of productive ideas within the firm. $\phi^O(\omega)$ summarizes the set of productive ideas that are outside in firms' markets and available to workers in the firm. Let $k_n(\omega)$ 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, $\phi^O(\omega) = \sum_n k_n(\omega)\lambda_n$ 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, Hopenhayn and Chari 1991). Thus, we directly model the dependence of learning returns on firm productivity, similar to recent literature (e.g., Monge-Naranjo 2016, Engbom 2020).

Learning also happens through interactions with the external environment. Firms may adjust their product requirements for different destinations (Verhoogen 2008, Manova and Zhang 2012), and managers can also get new ideas by learning from the local people they do business with or compete with (Buera and Oberfield 2020). The literature finds that the gains from trade-induced technology diffusion are several times of the static gains from trade (e.g., Alvarez et al. 2013, Sampson 2016, Buera and Oberfield 2020). It is natural to conjecture that workers' human capital may also embody trade-induced knowledge diffusion. Because the share of sales to each destination proxies the proportion of employees devoted to that destination, we thus weight exposure to destinations' knowledge by these sales shares.

3.1.2 Firms

Firm Productivity. There is a mass $\bar{M}$ of monopolistically competitive firms. Without loss of generality, we normalize $\bar{M} = 1$. Each firm ω draws productivity level $z(\omega)$ from distribution $\Phi(z)$, and firm productivity is time-invariant. Each firm produces a unique variety using labor. For a firm with productivity $z(\omega)$, producing one unit of good requires $1/z(\omega)$

efficiency labor. Varieties are internationally traded and aggregated into a nontradable final good in each country with a constant elasticity of substitution σ across varieties.

Trade Environment. There are $n = 1, 2, ..., N$ destination markets. We index the home country as the first market $n = 1$, and all other markets are foreign economies. We assume that the home country is a small open economy, meaning that aggregate variables in foreign countries are invariant to conditions at home. Due to monopolistic competition, the quantity demanded for firm ω in market n is $y_n(\omega) = p_n(\omega)^{-\sigma} P_n^{\sigma} Y_n$, 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 in market n is determined as $p_n(\omega) = y_n(\omega)^{-\frac{1}{\sigma}} P_n Y_n^{\frac{1}{\sigma}}$, and the revenue in market n is $p_n(\omega) y_n(\omega) = y_n(\omega)^{\frac{\sigma-1}{\sigma}} P_n Y_n^{\frac{1}{\sigma}}$. 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 no trade costs of selling to the home market, which means $\tau_1 = 1$ and $f_1 = 0$.

Costs of Hiring Workers. To hire workers, firms need to post vacancies to have chances of meeting workers. 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 $v(\omega)$ be the optimal amount of vacancies for firm ω, as detailed below. The total number of vacancies is $V = \int v(\omega) d\Phi(z(\omega))$. We define $F(z(\omega)) = \int_{z_{\min}}^{z(\omega)} v(\omega) d\Phi(z(\omega))/V$ as the offer distribution.

Firms' Revenue. Aggregating over destinations, we can compute the firm's total revenue (gross of fixed export costs) as $\sum_n I_n(\omega) y_n(\omega)^{\frac{\sigma-1}{\sigma}} P_n Y_n^{\frac{1}{\sigma}}$, where $I_n(\omega) \in \{0, 1\}$ indexes export decisions. When determining whether and how much to sell in each destination ($I_n(\omega)$ and $y_n(\omega)$), the firm will take into account: (1) total output given by $z(\omega)h(\omega)$, where $h(\omega) = \sum_a \int_{i \in \omega} (h_i^a - s^a(h_i^a, \omega)) di$ is the total amount of efficiency units used in firm ω's production, aggregated over workers of different ages; (2) the iceberg and fixed export costs; and (3) the impact of export destinations on workers' human capital, which affects the future job surplus. We will specify the problem of deciding export destinations in Section 3.3. With little abuse of notation, the revenue per unit of labor is $\tilde{z}(w) = \frac{\sum_n I_n(\omega) y_n(\omega)^{\frac{\sigma-1}{\sigma}} P_n Y_n^{\frac{1}{\sigma}}}{h(\omega)}$, which plays the role of labor productivity in our model.

3.2 Solving Worker's Wage and Human Capital Investment

3.2.1 Description of Bargaining Processes and Job-to-Job Moves

As described earlier, a worker's wage is $w_i^a(\omega) = r_i(\omega)\tilde{z}(\omega)(h_i^a - s^a(h_i^a, \omega))$, where the piece rate (proportion of revenues accruing to the worker), $r_i(\omega)$, is worker-firm-specific and depends on the worker-firm bargaining history. We now describe the processes regarding the determination of $r_i(\omega)$, following Cahuc et al. (2006). For ease of description, we denote the value as $V^a(r, h_i^a, \omega)$ for worker i of age a with piece rate r in firm ω. We denote the joint (worker + firm) value for the job as $M^a(h_i^a, \omega)$, which does not rely on r, as a lower piece rate r will be offset by a higher portion of revenues going to the firm, $1 - r$.

An Unemployed Searcher. When an unemployed person i meets and accepts a job at firm ω, the person is engaged in the Nash Bargaining with the employer over the job surplus $M^a(h_i^a, \omega)$. The outside option of the worker is the unemployment value defined as $V_U^a(h_i^a)$, whereas the outside option for the firm is set to 0. We assume that the worker's bargaining power is $0 < \beta < 1$. Thus, the piece rate, r, is determined by:

$$\max_r \left[V^a(r, h_i^a, \omega) - V_U^a(h_i^a)\right]^\beta \left[M^a(h_i^a, \omega) - V^a(r, h_i^a, \omega)\right]^{1-\beta}. \tag{7}$$

Solving this optimization problem implies the piece rate r satisfies,

$$V^a(r, h_i^a, \omega) = V_U^a(h_i^a) + \beta\left[M^a(h_i^a, \omega) - V_U^a(h_i^a)\right]. \tag{8}$$

This means that the worker obtains the outside value of unemployment plus a portion β of extra value of the job relative to unemployment, $M^a(h_i^a, \omega) - V_U^a(h_i^a)$. The formula of $V^a(r, h_i^a, \omega)$, $V_U^a(h_i^a)$, and $M^a(h_i^a, \omega)$ will be described below in Sections 3.2.2–3.2.3.

On-the-Job Searchers. After accepting the job, an employed person's piece rate r does not change over time until there is an outside offer from a poaching firm denoted by ω'. When there is an outside offer from a poaching firm during the job search, there are three scenarios which lead to different ways about how the employed person's piece rate is revised.

1. The poaching firm cannot offer the worker a value higher than the worker's current value, which means that $V^a(r, h_i^a, \omega) > M^a(h_i^a, \omega')$. In this case, the worker's wage will not be affected by the outside offer, and thus piece rate r does not change.

2. The job in the poaching firm ω' is more valuable than the worker's job in the current

firm ω, which means that $M^a(h_i^a, \omega') > M^a(h_i^a, \omega)$. In this case, the worker will move to the poaching firm. Now the worker will use the job value in the current firm $M^a(h_i^a, \omega)$ as the outside value. The piece rate r' earned by the worker in the poaching firm is also determined by the Nash Bargaining:

$$\max_{r'} \left[V^a(r', h_i^a, \omega') - M^a(h_i^a, \omega)\right]^\beta \left[M^a(h_i^a, \omega') - V^a(r', h_i^a, \omega')\right]^{1-\beta}. \tag{9}$$

Solving this problem implies the piece rate r' in the poaching firm ω' for worker i satisfies

$$V^a(r', h_i^a, \omega') = M^a(h_i^a, \omega) + \beta \left[M^a(h_i^a, \omega') - M^a(h_i^a, \omega)\right]. \tag{10}$$

3. Finally, we consider the scenario when the job in the current firm ω is more valuable than the job in the poaching firm ω', but the worker's value is so low that the poacher's offer is attractive to the worker, which means $M^a(h_i^a, \omega') < M^a(h_i^a, \omega)$ and $M^a(h_i^a, \omega') > V^a(r, h_i^a, \omega)$. In this scenario, to prevent the worker from leaving, the current firm would like to renegotiate with the worker over a new division of the job surplus. The worker now uses the poacher's job value $M^a(h_i^a, \omega')$ as the outside option. Thus, the worker stays in the current firm, and the new piece rate r' of the worker in the current firm is determined by the Nash Bargaining as in equation (7), except for a different outside value of the worker. This implies that the new piece rate r' of the worker satisfies

$$V^a(r', h_i^a, \omega) = M^a(h_i^a, \omega') + \beta \left[M^a(h_i^a, \omega) - M^a(h_i^a, \omega')\right]. \tag{11}$$

3.2.2 Worker's Value

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

$$
\begin{aligned}
V^a(r, h_i^a, \omega) = & \underbrace{r\tilde{z}(\omega)(h_i^a - s^a(h_i^a, \omega))}_{\text{current wage}} + \underbrace{\frac{(1-\kappa)(1-\lambda_E) + (1-\kappa)\lambda_E \int (1 - \mathbf{1}_{neg}) dF(z(\omega'))}{1+\rho} V^{a+1}(r, h_i^{a+1}, \omega)}_{\text{next-period value if the job is not exogenously separated and there is no negotiation}} \\
& + \underbrace{\frac{\kappa(1-\lambda_U)}{1+\rho} V_U^{a+1}(h_i^{a+1}) + \frac{\kappa\lambda_U}{1+\rho} \int V_U^{a+1}(h_i^{a+1}) + \beta \left[M^{a+1}(h_i^{a+1}, \omega') - V_U^a(h_i^{a+1}) \right] dF(z(\omega'))}_{\text{next-period value if the job is exogenously separated}} \\
& + \underbrace{\frac{(1-\kappa)\lambda_E}{1+\rho} \int \mathbf{1}_{neg} [(1-\beta)\{M^{a+1}(h_i^{a+1}, \omega'), M^{a+1}(h_i^{a+1}, \omega)\}^- + \beta \{M^{a+1}(h_i^{a+1}, \omega'), M^{a+1}(h_i^{a+1}, \omega)\}^+] dF}_{\text{next-period value if the job is not exogenously separated and worker-firm negotiation occurs}}, \\
\text{s.t.} \quad & \underbrace{h_i^{a+1} = (1-\delta_h) h_i^a + \phi^E(\omega) s^a(h_i^a, \omega)^\alpha}_{\text{human capital evolution}}.
\end{aligned} \tag{12}
$$

The specification $V^a(r, h_i^a, \omega)$ shows that workers' value relies on four state variables—age, contractual piece rate, human capital stock, and employer's productivity.[33] $\mathbf{1}_{neg}$ is a dummy variable indicating the occurrence of renegotiation with the current firm or negotiation with the poacher.[34] The first line of the equation captures the current wage, as well as the future value if the worker is not exogenously separated and does not face an attractive outside offer in the next period. The 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 or obtains a higher value if she can find a job immediately. Finally, the last line captures the future value if poaching happens with an attractive offer to the worker. As described earlier, there are two scenarios: (1) the current job continues, and the worker renegotiates with the current firm; or (2) the worker moves to the poaching firm and negotiates with the poaching firm. In either scenario, the worker will use value in the less-valuable job, $\{M^{a+1}(h_i^{a+1}, \omega'), M^{a+1}(h_i^{a+1}, \omega)\}^-$,[35] as the outside option to negotiate for a new rate r', and with the new piece rate r', the worker's value is a weighted average of the job values in the current and poaching firms, as shown by equations (10)–(11).

As discussed earlier, we assume that unemployment is equivalent to employment in the least productive firm: $V_U^a(h_i^a) = \min_\omega M^a(h_i^a, \omega)$.

[33] As we focus on the steady state, we omit aggregate state variables in specifying $V^a(r, h_i^a, \omega)$.

[34] This happens if the poacher's offer is attractive to the worker, $M^{a+1}(h_i^{a+1}, \omega') > V^{a+1}(r, h_i^{a+1}, \omega)$.

[35] $\{M^{a+1}(h_i^{a+1}, \omega'), M^{a+1}(h_i^{a+1}, \omega)\}^-$ is the minimum of $M^{a+1}(h_i^{a+1}, \omega')$ and $M^{a+1}(h_i^{a+1}, \omega)$, and $\{M^{a+1}(h_i^{a+1}, \omega'), M^{a+1}(h_i^{a+1}, \omega)\}^+$ is the maximum of $M^{a+1}(h_i^{a+1}, \omega')$ and $M^{a+1}(h_i^{a+1}, \omega)$.

Solving Piece Rate from Bargaining. Note that in equation (12), the worker's value is a function of piece rate r. In light of the bargaining processes in Section 3.2.1, the firm and the worker will choose a specific piece rate r that delivers the same worker's value as specified by the bargaining outcome.[36]

3.2.3 Job Value and Human Capital Investment

Job Value. To solve for human capital investments, we need to first specify the joint (firm + worker) value of a job. For a worker-firm match, the job value is given by:

$$
\begin{aligned}
M^a(h_i^a, \omega) = & \underbrace{\tilde{z}(\omega)(h_i^a - s^a(h_i^a, \omega))}_{\text{current revenue}} + \underbrace{\frac{(1-\kappa)(1-\lambda_E) + (1-\kappa)\lambda_E \int (1 - \mathbf{1}_{move}) dF(z(\omega'))}{1+\rho} M^{a+1}(h_i^{a+1}, \omega)}_{\text{next-period value if the job continues}} \\
& + \underbrace{\frac{\kappa(1-\lambda_U)}{1+\rho} V_U^{a+1}(h_i^{a+1}) + \frac{\kappa\lambda_U}{1+\rho} \int V_U^{a+1}(h_i^{a+1}) + \beta(M^{a+1}(h_i^{a+1}, \omega') - V_U^a(h_i^{a+1})) dF(z(\omega'))}_{\text{next-period value if the job is exogenously destructed}} \\
& + \underbrace{\frac{(1-\kappa)\lambda_E}{1+\rho} \int \mathbf{1}_{move} [M^{a+1}(h_i^{a+1}, \omega) + \beta(M^{a+1}(h_i^{a+1}, \omega') - M^{a+1}(h_i^{a+1}, \omega))] dF(z(\omega'))}_{\text{next-period value if the worker moves to the poacher}}, \\
\text{s.t.} \quad & \underbrace{h_i^{a+1} = (1-\delta_h) h_i^a + \phi^E(\omega) s^a(h_i^a, \omega)^\alpha}_{\text{human capital evolution}}.
\end{aligned}
\tag{13}
$$

$\mathbf{1}_{move}$ is a dummy variable indicating the occurrence of job-to-job moves.[37] The first line captures the production value in the current period, as well as the next-period job value if the worker stays in the firm. The second line shows the future worker's value if the job is exogenously destructed. In this case, the worker enjoys the unemployment value and may find a job immediately. Finally, the last line captures the future value if the worker moves to a poaching firm. The worker will use the current job's value as an outside option and get an extra surplus as the poacher values the worker better.

The difference between the job value and the worker's value is the firm's value from the job, which mainly captures the portion of current and future revenues (generated by the

[36] Cahuc et al. (2006) analytically solve for the piece rate and show that it increases with the worker's outside option, which relies on the history of the outside offers received by the worker. However, our model with endogenous human capital formation does not yield an analytical solution of the piece rate.

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

worker) accruing to the firm owner.

Human Capital Investment. We assume that the worker and the firm will choose the time spent on human capital accumulation, $s^a(h_i^a, \omega)$, to maximize the joint job surplus $M^a(h_i^a, \omega)$ (Acemoglu and Pischke 1999). By applying the first-order condition of equation (13) with regard to $s^a(h_i^a, \omega)$ as well as the evolution of human capital $h_i^{a+1} = (1-\delta_h)h_i^a + \phi^E(\omega)s^a(h_i^a, \omega)^\alpha$, we obtain:

$$s^a(h_i^a, \omega) = \left(\frac{\alpha \phi^E(\omega)}{\tilde{z}(\omega)} \frac{\partial M^a(h_i^a, \omega)}{\partial h_i^{a+1}} \right)^{\frac{1}{1-\alpha}}. \tag{14}$$

The optimal time spent on human capital accumulation increases with marginal benefits, which are determined by human capital increment per time $\phi^E(\omega)$ and the marginal return of new human capital $\frac{\partial M^a(h^a,\omega)}{\partial h^{a+1}}$. Exporting to destinations with high knowledge stocks will lead to a higher value of $\phi^E(\omega)$ and thus encourage human capital investment. Moreover, as workers become older, the gains of human capital accumulation tend to decline. In particular, for a worker retiring at the end of this period (the next-period value is 0), $\frac{\partial M^a(h^a,\omega)}{\partial h^{a+1}} = 0$, and therefore there is no human capital investment. With this feature, our model is able to numerically generate little experience effects in the final working years.

3.3 Solving Firm's Export Destinations and Vacancy Posting

3.3.1 Export Destinations

To account for the impact of firms' export destinations on workers' human capital accumulation, we consider that the firm's export destinations are chosen to maximize the total job value aggregated over workers within the firm, net of fixed export costs:

$$\begin{aligned}
&\max_{\{I_n(\omega), y_n(\omega)\}} \sum_a \int_{i \in \omega} M^a(h_i^a, \omega) di - \sum_n I_n(\omega) P_1 f_n \\
&= \underbrace{\sum_n I_n(\omega) \left(y_n(\omega)^{\frac{\sigma-1}{\sigma}} P_n Y_n^{\frac{1}{\sigma}} - P_1 f_n \right)}_{\text{revenues net of fixed export costs}} + \underbrace{\sum_a \int_{i \in \omega} M^{a,future}(h_i^a, \omega) di}_{\text{future job value}} \\
&s.t. \ \sum_n I_n(\omega) \tau_n y_n(\omega) = z(\omega) h(\omega)
\end{aligned} \tag{15}$$

$I_n(\omega) \in \{0, 1\}$ indexes export decisions. The second line is obtained by dividing the job value $M^a(h_i^a, \omega)$ into the current revenue and the future value $M^{a,future}(h_i^a, \omega)$.[38] Compared with the static problem of maximizing trade revenues net of fixed costs (Melitz 2003), we also take into account the impact of export destinations on the future job value through workers' human capital, by incorporating workers' future value into the choice of export destinations.

In the presence of convex vacancy costs, firms face increasing marginal costs of hiring workers, and thus firms' export decisions are interdependent across destination markets. Thus, our model implies a permutation problem for deciding the set of export destinations from all feasible combinations, similar to Tintelnot (2017) who studies the permutation problem of how to structure multinational production. In total, there are $2^N - 1$ feasible combinations of destination markets ($I_n(\omega) \in \{0, 1\}$ for each market $n = 1, ..., N$). To solve the choice of export destinations, we first evaluate the benefit in equation (15) given each feasible combination of export destinations[39] and then choose the optimal combination of export markets that delivers the highest benefit.

3.3.2 Firm's Vacancy Choices

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

$$
\begin{aligned}
c_v v(\omega)^{\gamma_v} P_1 = & \sum_a \frac{\lambda_U(1-\beta)}{V} \int \left[M^a(h^a, \omega) - V_U^a(h^a)\right] D_U^a(h^a) dh^a \\
& + \sum_a \frac{\lambda_E(1-\beta)}{V} \int \int \max\{M^a(h^a, \omega) - M^a(h^a, \omega'), 0\} D^a(h^a, \omega') dh^a d\Phi(z(\omega')).
\end{aligned}
\tag{16}
$$

Here $D_U^a(h^a)$ is the measure of unemployed workers with human capital h^a, and $D^a(h^a, \omega)$ is the measure of employed workers with human capital h^a and at firm ω.[40] The left-hand side captures the marginal costs of posting a vacancy. The right-hand side captures the aggregate value per vacancy from hiring unemployed workers and poaching employed workers from other firms, with $(1 - \beta)$ governing the firm's share of the increment in surplus from hiring.

[38] Specifically, we have $M^{a,future}(h_i^a, \omega) = M^a(h_i^a, \omega) - \tilde{z}(\omega)(h_i^a - s^a(h_i^a, \omega))$.

[39] Given each combination of export destinations, we also need to solve the amount of output sold to each destination involved. In the absence of the future value in equation (15), for each set of values $\{I_n(\omega)\}_{n=1,...,N}$, this amount can be solved analytically as $y_n(\omega) = \frac{I_n(\omega) P_n^\sigma Y_n \tau_n^{-\sigma}}{\sum_{n'=1}^N I_{n'}(\omega) P_{n'}^\sigma Y_{n'} \tau_{n'}^{1-\sigma}} z(\omega) h(\omega)$. With the future benefit in equation (15), we need to numerically solve the amount of output sold to each destination.

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

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.[41] We abstract away from saving, and all the firm profits (revenues accruing to the firm net of fixed export costs) 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 as follows:

Definition 1 *The general equilibrium consists of meeting rates* $\{\lambda_E, \lambda_U\}$*, employment distributions* $\{D_U^a(h^a), D^a(h^a, \omega)\}$*, firms' export destinations and revenues* $\{y_n(\omega), I_n(\omega), \tilde{z}(\omega)\}$ *and vacancy posting* $v(\omega)$*, the worker-firm joint decision of human capital accumulation* $s^a(h_i^a, \omega)$*, each worker's piece rate* $r_i(\omega)$*, and aggregate price and quantity variables in the home country* $\{P_1, Y_1\}$*. These variables satisfy:*
(1) each worker's piece rate $r_i(\omega)$ *satisfies the bargaining processes specified in Section 3.2.1;*
(2) the worker-firm joint decision of human capital accumulation $s^a(h_i^a, \omega)$ *is given by equation (14), which maximizes the job value specified by equation (13);*
(3) firms' export destinations and revenues $\{y_n(\omega), I_n(\omega), \tilde{z}(\omega)\}$ *are given to maximize the benefit in equation (15), given employment distributions and aggregate price and quantities;*
(4) firms' optimal vacancy postings $v(\omega)$ *are given by equation (16);*
(5) meeting rates $\{\lambda_E, \lambda_U\}$ *are determined by unemployment rate* $U = \sum_a \int D_U^a(h^a)dh^a$ *and the total amount of vacancies* $V = \bar{M} \int v(\omega) d\Phi(z(\omega))$*;*
(6) employment distributions $\{D_U^a(h^a), D^a(h^a, \omega)\}$ *are consistent with revenues* $\tilde{z}(\omega)$*, vacancies* $v(\omega)$*, and the worker-firm joint decision of human capital accumulation* $s^a(h_i^a, \omega)$ *across all workers within the firm* $i \in \omega$*; and*
(7) 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 worker i at firm ω can be written as:

$$\log w_i^a(\omega) = \underbrace{\log h_i^a}_{\text{human capital}} + \underbrace{\log\left(1 - \frac{s^a(h_i^a, \omega)}{h_i^a}\right)}_{\text{share of working time}} + \underbrace{\log \tilde{z}(\omega)}_{\text{labor productivity}} + \underbrace{\log r_i(\omega)}_{\text{piece rate}}. \tag{17}$$

[41] 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:

$$\Delta \log w_i^a(\omega) = \underbrace{\Delta \log h_i^a}_{\text{changes in human capital}} + \underbrace{\Delta \log \left(1 - \frac{s^a(h_i^a, \omega)}{h_i^a}\right)}_{\text{changes in working time}} + \underbrace{\Delta \log \tilde{z}(\omega)}_{\text{changes in labor productivity}} + \underbrace{\Delta \log r_i(\omega)}_{\text{changes in piece rate}} . \tag{18}$$

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 Townsend 2021, Buera, Kaboski and Yongseok 2021), by implementing alternative realizations of export costs to each firm in the steady state.

According to equation (18), 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 shown in 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 wage profiles through the human capital channel. Second, due to changes in human capital investment, workers' working time also changes. As young workers spend more time on human capital accumulation than old workers, working time is upward sloping over the lifecycle, and thus changes in working time would naturally alter wage profiles. Finally, export activity can change workers' bargaining positions in the process of wage determination. In our model, despite no direct impact on firms' inherent productivity $z(\omega)$, export activity generally changes firms' labor productivity $\tilde{z}(\omega)$, as it is increasingly costly to hire new workers, and thus increased demand due to exporting may lead to large revenues per worker. Labor productivity changes are identical for young and old workers within a firm and thus do not directly affect our construction of wage profiles. However, increased labor productivity offers larger room for the current workers' wages to grow through wage renegotiations when these workers are poached by outside firms, 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 *Suppose that meeting and separation rates $\lambda_U = 1$ and $\kappa = 1$, unemployment value $V_U^a(h_i^a) = 0 \; \forall \; i, a$,*[42] *discount rate ρ is large enough, and vacancy costs are linear $\gamma_v = 0$. The gains from trade are:*

$$GT = \underbrace{\Pi_d^{-\frac{1}{\sigma-1}}}_{\textit{changes in real income per efficiency labor}} \times \underbrace{\frac{\bar{h}}{\bar{h}^{aut}}}_{\textit{changes in average efficiency labor per employee}} . \quad (19)$$

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

Proof: See Appendix F.1. □

We obtain Proposition 1 under several assumptions for analytical tractability. The meeting and separation rates $\lambda_U = 1$ and $\kappa = 1$ ensure full employment and that firms behave like hiring in a spot market in each period, which resembles the typical assumption in the Melitz model (Melitz 2003).[43] The assumptions of unemployment value $V_U^a(h_i^a) = 0$ and large discount rate ρ imply that firms obtain a proportion $(1 - \beta)$ of revenues, and that time spent on human capital accumulation is relatively little. The assumption of $\gamma_v = 0$ implies that marginal costs of hiring remain constant, and thus export decisions across destinations are independent. All these assumptions will be relaxed quantitatively, but as shown below, the formula in Proposition 1 still provides a good approximation of our quantitative result.

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

[42] 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 modeling the unemployment disutility by following Bagger et al. (2014) to conveniently assume that the unemployment value is equivalent to the employment value in the least productive firm, as discussed in Section 3.2.

[43] 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 include the effects of wage renegotiations numerically.

would produce aggregate welfare effects. Moreover, the typical Melitz force can also reinforce the gains in employees' average efficiency labor, as trade induces workers' reallocation toward exporters where workers may enjoy faster human capital accumulation.

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. As discussed earlier in Section 3.5, within-job wage profiles in our model reflect changes in human capital accumulation as well as changes in worker-firm bargaining positions due to wage renegotiations. Thus, the core variables that we use are job-to-job transitions and the slope of wages on firm employment size, which are informative of on-the-job search intensity and workers' bargaining power, governing the strength of wage renegotiations. Combining information on wage renegotiations, we use the within-job wage profiles to discipline 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, and non-high-income countries in Europe, Asia, North America, Africa, and South America.[44]

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

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

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 shocks in each period, because modeling both labor market dynamics and stochastic changes in firm exports makes the model intractable.[45] Finally, it is common 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.[46]

The calibration must determine the following parameter values: worker's lifetime A, discount rate ρ, the number of destinations N, the parameters of labor search processes and wage negotiations $\{\phi, c_M, \kappa, \eta, \beta\}$, 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 $A = 40$ years.

We set the elasticity of job matches to vacancies to $\phi = 0.3$ following Shimer (2005)'s estimate for the U.S. 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, we use

[45] 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 their different export statuses.

[46] In a standard Melitz-Chaney model with a competitive labor market (Chaney 2008), $\zeta > \sigma - 1$ is required to ensure that the aggregation of sales across firms is finite. Compared with the standard model, our model has two main differences (labor market frictions and human capital accumulation) that may loosen or tighten this requirement. Given the difficulty to analytically solve the exact requirement for the finite aggregation of sales in our model, we require $\zeta > \sigma - 1$ in the calibration.

Table 4: Parameters Set without Solving the Model

Parameter	Notation	Value	Source
Total working time (years)	A	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	1.5	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.

$\gamma_v = 1.5$ according to Dix-Carneiro et al. (2019)'s estimate for Brazilian 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 using the method of moments. 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 average of reduced-form evidence based on the matching estimator 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 (18), export entry leads to changes in the increment of human capital per time spent, changes in time allocated to working, and higher labor revenues that affect wage profiles by widening the scope of wage renegotiations. We relegate the computation details to Appendix G.1.

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. 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

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 increment	μ	0.07
Constant in vacancy costs	c_v	0.02
Workers' bargaining power	β	0.60
Elast. of human capital increment to productivity	γ_1	0.27
Elast. of human capital increment to market knowledge	γ_2	0.21
Shape parameter of productivity distribution	ζ	4.10
Export demand (by destination, $n = 2, ..., N$)	$P_n^\sigma Y_n \tau_n^{1-\sigma}$	37.86 (24.47)
Export fixed costs (by destination, $n = 2, ..., N$)	$\bar{f}_n$	0.28 (0.19)
Std of export costs	σ_f	1.48
Import demand	$\bar{M}^I (p^I)^{1-\sigma}$	0.14

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.

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 increment 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 increment on firm productivity (γ_1) and the knowledge stock in destination markets (γ_2), respectively.[47]

4.3 Calibration 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 based on a bargaining model with wage

[47]Because of no direct correspondences between $\{\gamma_1, \gamma_2\}$ and the data, our estimation thus relies on the indirect inference (Gouriéroux and Monfort 1996), where the econometrican seeks the structural parameters to minimize the distance between the estimates from econometric models on the real data and the estimates from the same econometric models estimated on the simulated data. Appendix Table A.13 reports the Jacobian matrix of how changes in γ_1 and γ_2 affect the moments and confirms that the slope of experience returns on firm employment is mostly responsive to γ_1, while the change in experience returns due to export entry into high-income countries is mostly responsive to γ_2.

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

Notes: The results for the share of exporters and the ratio of exports to firms' total sales refer to the average across all the foreign destinations, with the standard deviation in 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 firm employment) by regressing log wage on the exporter dummy (log firm employment), individual fixed effects, and year fixed effects. Finally, we construct experience returns (to 20 years of experience) in the same way as in Section 2.3. We compute exporters' (non-exporters') employment-weighted experience returns, by averaging experience returns across exporters (non-exporters), using each firm's employment as weights. Experience returns with regard to export entry are the average of reduced-form evidence in Tables 3 and A.12.

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 firm data from Germany. 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. 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 A.12.

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 service firms surveyed by the World Bank. Consistent with our analysis of the RAIS data, we restrict the ES to manufacturing firms with at least 10 employees, with totally 1,140 firms in the sample.

The ES reports the share of workers that receive formal training and does not incorporate other forms of human capital accumulation (such as learning from supervisors). Despite the lack of a direct correspondence between the ES training data and our model, it is still a good exercise to check whether the (unit-free) elasticity of learning intensity to employment size is similar between the model and the data. As we cannot take the logarithm of the share of trained workers (many firms report 0%) in the ES, we divide firms (ranked by employment) into 50 equally sized bins and then regress the logarithm of the share of trained workers on log average firm size across bins. In the model, we divide the firm employment distribution into 50 equally sized bins and regress the logarithm of average time spent on human capital accumulation on log average firm size across bins.[48]

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 elasticity of learning intensity to firm employment size is smaller in our model than in the actual data. One possible reason for this difference is that small firms are more involved in informal training, whereas the ES only reports the formal training.[49]

[48] 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.

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

Table 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)	0.209***	0.192***	0.104***	0.083***
	(0.029)	(0.062)	(0.010)	(0.025)
Share of exporters		0.116		0.045
		(0.380)		(0.049)
Obs	50	50	50	50
R-squared	0.626	0.626	0.839	0.844

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

4.6 Decomposing the Returns to Experience

With the calibrated model, we now turn to understand what shapes experience-wage profiles. Figure 4a presents the overall experience-wage profiles (averaged across firms) and decomposes them into different factors. Human capital accumulation accounts for about 70% of workers' overall wage growth over the lifecycle. Figure 4b shows that human capital is still an important factor behind the difference in workers' lifecycle wage growth between exporters and non-exporters. However, because of the diminishing returns of human capital investment, the contribution of human capital growth to explaining the difference (55%) is smaller than the role of human capital in explaining the overall wage profiles shown in Figure 4a, whereas the contribution of changes in working time becomes larger.

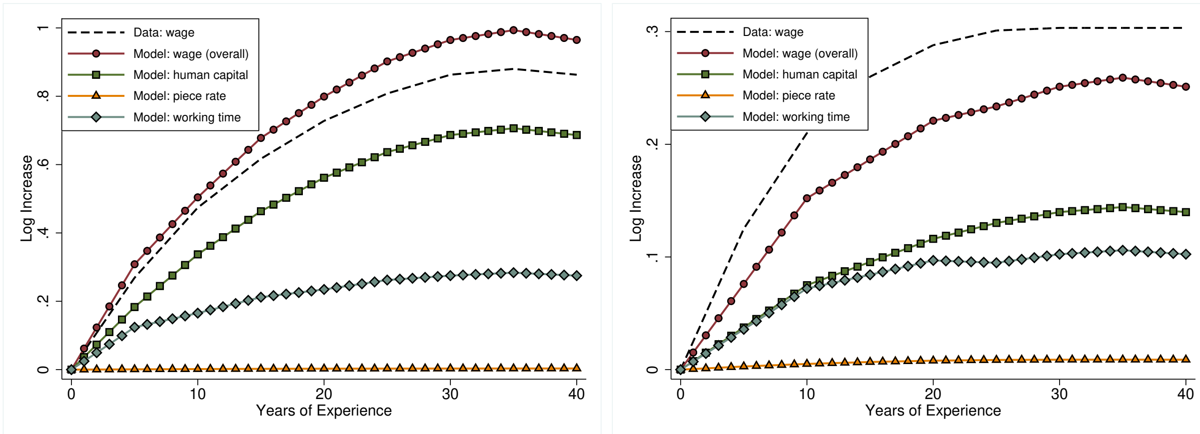
Table 8: Changes in Returns to 20 Years of Experience due to Export Entry

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

Notes: The data on experience returns with regard to export entry is the average of reduced-form evidence in Tables 3 and A.12 based on the matching estimator. The percentage in brackets refers to the contribution of each channel to the overall model-generated change.

Table 8 presents the decomposition of changes in returns to experience due to export entry. We find that human capital accounts for half of the gains in experience returns after entry to high-income countries. Finally, entry into non-high-income destinations is associated with negative returns in experience returns, as exporting to non-high-income destinations

Figure 4: Decomposing the Returns to Experience



(a) Overall Experience-wage Profiles

(b) Difference btw Exporters/non-exporters

Notes: The data on experience returns are computed according to Section 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.

may reduce the increment in human capital per time, and higher revenues per labor following export entry also increase the opportunity costs of investing in human capital.[50]

Our quantitative model finds a small role of changes in worker-firm rent sharing (measured by piece rates) in explaining the wage profiles, in line with Arellano-Bover and Saltiel (2021) who show that in Brazil, returns to experience are not much different between all workers and the sample of displaced workers who lose bargaining positions. This quantitative finding is mainly driven by a high value of workers' wage bargaining power ($\beta = 0.6$): As workers already gain good bargaining positions when hired, there is relatively small room for workers' wages to grow through wage negotiations when workers are poached. In Section 5.3.1, we show that with a low value of workers' wage bargaining power, the role played by changes in worker-firm rent sharing in determining wage profiles becomes much more important.

5 Quantitative Evaluation

In this section, we apply our calibrated model to study the role of human capital formation in shaping the gains from trade and how this role depends on export destinations. We then

[50]It is worth noting that the changes in experience returns after entry into non-high-income destinations are estimated with much noise in the data. Our model-generated changes in experience returns after entry into non-high-income destinations are similar in magnitude to the reduced-form evidence based on the event study in Appendix Figure A.3.

provide robustness checks regarding model assumptions and parameters.

5.1 Gains from Trade

Table 9 reports the gains from trade, computed as the ratio of real consumption in the calibrated model to that in the autarkic economy where we set Brazil's bilateral trade costs with foreign economies to infinity. The overall gains from trade are 7.78%. Consistent with Proposition 1,[51] both more human capital and higher real income per efficiency labor contribute to the gains from trade, with a 3.98% and 3.75% increase in real income respectively. As we allow for unemployment quantitatively, trade openness increases firms' overall vacancy postings, which also leads to a 0.51% employment gain. Finally, as workers invest more time in human capital accumulation, the average working time (one minus the share of human capital investment in total human capital) decreases by 0.46% after trade openness.

Table 9: Gains from Trade

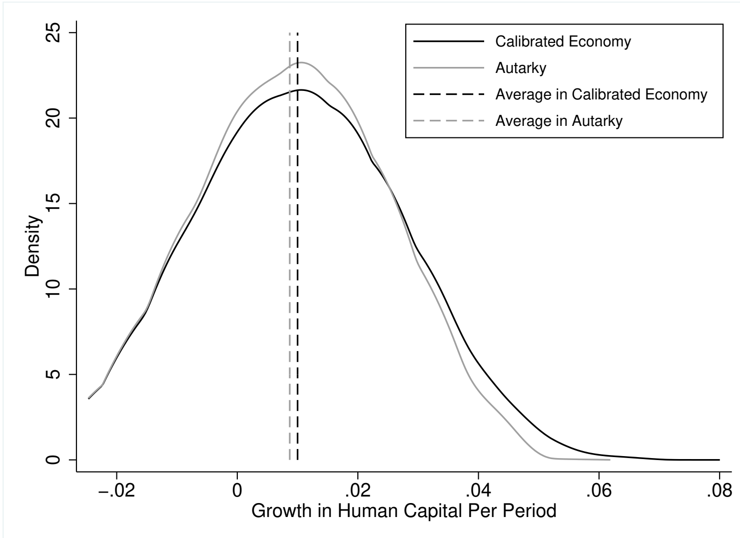
Changes in Real Income from Autarky to the Calibrated Economy			7.78%
Decomposition:			
	Real Income Per Employee		
Employment	Income Per Efficiency Labor	Human Capital	Working Time
0.51%	3.75%	3.98%	-0.46%

5.2 Export Destinations and Human Capital Formation

Our empirical evidence and model highlight the potential importance of export activity and especially export destinations in affecting human capital formation. To further understand this force quantitatively, we first provide a decomposition of the change in human capital growth after trade openness and then perform two additional counterfactual exercises.

[51] If we directly apply the formula for the gains from trade in Proposition 1, the gains from trade are 7.73%, similar to the overall gains from trade (7.78%). This indicates that changes in human capital and real income per efficiency labor can account for most of the gains from trade, and therefore the formula in Proposition 1 provides a good approximation of our quantitative finding. Given that Proposition 1 is derived under strict assumptions on labor market frictions, Appendix Section G.2 provides a discussion of how strictly imposing such assumptions affects the gains in human capital from trade.

Figure 5: Distribution of Human Capital Growth



5.2.1 Decomposition of Human Capital Growth

Figure 5 compares the distribution of workers' human capital growth between autarky and the calibrated economy, indicating faster human capital growth after trade openness. Motivated by decomposition of productivity growth (Foster et al. 2001), we decompose changes in human capital growth after trade openness to reflect the contributions of different forces. Denote the average per-period human capital growth in the economy as g_h.

$$g_h = \int l(z) g_h(z) d\Phi(z), \tag{20}$$

where $l(z)$ is firm z's employment share, and $g_h(z)$ is average growth in human capital per period at firm z. Thus, the changes in growth of human capital can be written as:

$$g_h^{'} - g_h = \int \underbrace{[l^{'}(z) - l(z)][g_h(z) - g_h]}_{\text{between-firm term}} + \underbrace{l(z)[g_h^{'}(z) - g_h(z)]}_{\text{within-firm term}} + \underbrace{[l^{'}(z) - l(z)][g_h^{'}(z) - g_h(z)]}_{\text{cross-firm term}} d\Phi(z). \tag{21}$$

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

Table 10 reports the decomposition results. Between-firm term contributes slightly to the increase in human capital growth, reflecting the trade-induced labor reallocation toward more productive firms as shown in Melitz (2003). The within-firm term contributes the most to the overall increase in human capital growth from autarky to the calibrated economy.

Table 10: Changes in Human Capital Growth

(a) Changes in human capital growth from autarky to the calibrated economy			
Overall	Between-firm Term	Within-firm Term	Cross-firm Term
0.12%	0.01%	0.09%	0.02%
(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%	0.08%	-0.02%	0.06%

Panel (b) of Table 10 further decomposes the within-firm term according to firms' export status in the calibrated economy. Consistent with relatively higher knowledge stocks in high-income destinations compared with Brazil, firms that solely export to high-income destinations contribute the most to the increase in human capital growth from autarky to the calibrated economy, followed by firms that export to both high-income and non-high-income destinations. Non-exporters and exporters that only sell to non-high-income countries contribute negatively to the within-firm term.[52] This result confirms that high-income destinations are associated with increased human capital formation.

5.2.2 Model with Identical Firm Learning Returns

We now compare our baseline model to a model with no trade-induced changes in human capital increment per time. According to human capital increment per time $\mu z(\omega)^{\gamma_1}\left(\phi^O(\omega)\right)^{\gamma_2}$ in equation (6), γ_1 decides the elasticity of human capital increment per time to firm productivity, governing how trade-induced labor reallocation across firms affects human capital increment; and γ_2 governs the elasticity of human capital increment per time to destinations' knowledge $\phi^O(\omega)$, shaping how entry into export destinations affects human capital increment. We now set $\gamma_1 = \gamma_2 = 0$ such that all firms have the same human capital increment and recalibrate this alternative model to the targeted data moments in Table 6.

Table 11 reports the results. This alternative model predicts that more productive firms and entry into high-income destinations are associated with negative changes in experience returns, which is inconsistent with the data. This is because higher revenues per labor (due to higher firm productivity or export entry) would raise opportunity costs of human capital investment and lead to lower investment levels. In contrast, in the baseline model

[52] 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: Comparing Baseline Model to Model with Identical Firm Learning Returns

	Slope of Experience Returns on Firm Size	ΔExperience Returns (after entry into high-income dests)	Gains from Trade: Real Income	Gains from Trade: Human Capital
(1) Data	0.15	0.22		
(2) Baseline model	0.15	0.21	7.78%	3.98%
(3) Model with identical firm learning returns, $\gamma_1 = \gamma_2 = 0$	-0.20	-0.03	5.05%	0.17%

Notes: Because parameters γ_1 and γ_2 are mainly disciplined by the slope of experience returns on firm size as well as changes in experience after export entry, we drop these two targeted moments when we recalibrate the alternative model with identical firm learning ($\gamma_1 = \gamma_2 = 0$) to understand how this alternative model predicts these two moments (the results are similar if we include these two moments into the targeted moments in the recalibration process). The alternative model matches all other targeted moments in Table 6 well.

with $\gamma_1 > 0$ and $\gamma_2 > 0$, human capital increment per time increases with firm productivity and destinations' knowledge levels, offsetting the effects of opportunity costs. This result highlights the importance of modeling the dependence of human capital increment on firm productivity and destinations' knowledge in matching changes in experience returns across firms and after export entry. Finally, the gains in human capital from trade are negligible in this alternative model, as trade does not directly affect human capital increment per time.[53]

5.2.3 Trade Liberalization with Different Destinations

Finally, given the vastly different knowledge stocks in different destinations, we explore how the effects of trade liberalization vary across destinations. In the first two rows of Table 12, we compute 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. Lowering trade costs to high-income destinations by 10% would increase Brazil's real income by 1.78%, largely due to a 1.38% increase in workers' average human capital. Surprisingly, lowering trade costs to non-high-income destinations by 10% would reduce Brazil's real income by 0.13%. This reduction is mainly driven by a 0.74% decline in workers' average human capital, as higher demand from non-high-income destinations makes productive firms to reallocate labor away from serving high-income export destinations, and higher revenues per labor due to exporting also increase the opportunity costs of investing in human capital. It is worth noting as we focus on comparing steady states and abstract from transitional dynamics

[53] In this alternative model, the slight gains in human capital from trade are partly due to that trade openness encourages more job vacancies and reduces duration of unemployment, which facilitates human capital formation.

Table 12: 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	1.78%	1.38%
Non-high-income	0.053	1.10	-0.13%	-0.74%
By main export destinations:				
Euro & U.S.	0.070	3.60	1.28%	1.07%
China (2019)	0.069	1.19	0.10%	-0.59%
South America	0.032	1.12	-0.12%	-0.49%

(computationally intractable), it is possible that lowering trade costs to non-high-income destinations leads to short-run gains due to changes in wages and prices.

In the last three rows of Table 12, we report changes in real income and human capital after a 10% decline in Brazil's export trade costs to main export destinations respectively.[54] In line with our previous results on high-income countries, lowering trade costs to Europe and the U.S. 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 in human capital levels.

5.3 Robustness Checks

5.3.1 Alternative Parameterization

We provide several robustness checks on how the key parameters regarding human capital formation and worker-firm rent sharing affect the gains in human capital from trade, as summarized by Table 13.

In the first exercise, we change the depreciation rate of human capital from $\delta_h = 0.02$ (baseline calibration) to $\delta_h = 0.01$, according to evidence on the 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.

[54] 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 B.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.

Therefore, compared with baseline results, trade-induced human capital investment faces stronger diminishing returns and results in smaller gains in human capital from trade.

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

In the third exercise, we change workers' bargaining power from $\beta = 0.6$ in the baseline to $\beta = 0$, an extreme scenario considered in Fajgelbaum (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 become smaller.

For each exercise, the last three columns in Table 13 report the decomposition of changes in within-job experience returns (after entry into high-income destinations) into different factors. We find the contribution of wage negotiations is quite sensitive to workers' bargaining power β. In our baseline model, with a high calibrated value of workers' bargaining power ($\beta = 0.6$), workers already have good bargaining positions when hired, and there is small room for workers' wages to grow through wage negotiations. However, with a low value of workers' bargaining power ($\beta = 0$), there is much larger room for wage negotiations, as workers start with low bargaining positions and use poachers as the outside option to gain better bargaining positions.[55] We find that changing on-the-job search intensity (poaching rate) also considerably affects the contribution of wage negotiations, as workers can trigger negotiations more often when they are poached more.

5.3.2 Model with Learning-by-doing

In our model, all human capital growth requires endogenous human capital investment à la Ben-Porath, whereas human capital may also be acquired through learning-by-doing (LBD). Appendix Section F.2 presents the model extension to consider that all human capital comes

[55] As shown in Section 3.2, 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.

Table 13: Robustness Checks

	Gains from Trade		Decomposing ΔExperience Returns (after entry into high-income dests)		
	Real Income	Human Capital	Human Capital	Piece Rate	Working Time
(1) Baseline	7.78%	3.98%	52%	5%	43%
Alternative parameterization:					
(2) HC depreciation rate $\delta_h = 0.01$	7.00%	2.59%	37%	6%	57%
(3) On-job search intensity $\eta = 0.4$	8.08%	4.07%	39%	18%	43%
(4) Workers' bargaining power $\beta = 0$	6.97%	2.13%	28%	44%	28%
Alternative assumptions:					
(5) Model with LBD	9.45%	5.72%	93%	7%	0%

Notes: "LBD" is short for "learning-by-doing." The last three columns compute the contribution of each factor to changes in returns to 20 years of experience (after entry to high-income destinations), in the same way as in Table 8.

from LBD, and that the human capital processes can potentially vary across firms and ages (e.g., Bagger et al. 2014, Gregory 2019). We recalibrate the parameters of this extended model to match all the targeted moments in Table 6.

The last row in Table 13 reports that the gains in human capital from trade are 5.72% in the LBD model, compared with 3.98% in the baseline model. Although it is difficult to quantitatively determine the portions of human capital coming from investment and LBD, we view these two results as informative of upper and lower bounds of the gains in human capital from trade. With no time costs of human capital accumulation, the LBD model attributes most of changes in wage profiles (due to export entry) to human capital growth and thus provides an upper bound for the gains in human capital from trade. On the other hand, in our model, human capital formation relies on endogenous choices of time spent on learning. As young workers spend more time on learning than old workers, working time is upward sloping over the lifecycle. This upward trend in working time over the lifecycle would naturally explain a portion of experience-wage profiles. Thus, compared with the LBD model, our baseline model attributes a smaller portion of lifetime wage profiles to human capital growth, thus leading to a more conservative assessment about the role of human capital in shaping the gains from trade.

6 Conclusion

Using Brazilian administrative 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 interpret the data and conduct experiments, we develop and quantify a model with firms' export market entry, worker-firm wage bargaining, and workers' human capital accumulation. In the model, workers' within-job wage grows due to human capital growth, changes in time allocated to working, and wage renegotiations. Particularly, we consider that human capital increment per time spent may depend on export destinations. We calibrate the model and find that human capital growth can explain roughly 50% of the 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 suggests that the increased human capital per worker accounts for one-half of the overall gains in real income from trade.

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 export markets. A fruitful area for future study is how this interaction impacts workers' income levels and inequality in countries with different development levels, which will ultimately lead to a better evaluation of the welfare impact of globalization.

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Appendix for Online Publication

A Appendix Tables and Graphs

Table A.1: Wage Profiles and Control Variables

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

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 in the upper 10% of firm employment distribution within each industry-year. Robust standard errors are in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

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

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

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: 1) average years of schooling; 2) the share of workers with high-school degrees; 3) the share of cognitive workers; 4) the share of production workers; 5) average workers' age; 6) firm employment size; and 7) firm employment percentiles (divided into 10 bins) within each industry-year bin. Robust standard errors are in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Table A.3: Wage Profiles and Firm Characteristics (Assuming Last 5 Years with No Experience Returns)

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

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: 1) average years of schooling; 2) the share of workers with high-school degrees; 3) the share of cognitive workers; 4) the share of production workers; 5) average workers' age; 6) firm employment size; and 7) firm employment percentiles (divided into 10 bins) within each industry-year bin. Robust standard errors are in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Table A.4: Average Wage Growth and Firm Characteristics

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

Note: The baseline group is non-exporters. The controls (specific to each experience bin in each firm and year) are: 1) average years of schooling; 2) the share of workers with high-school degrees; 3) the share of cognitive workers; 4) the share of production workers; 5) average workers' age; 6) firm employment size; and 7) firm employment percentiles (divided into 10 bins) within each industry-year bin. Robust standard errors are in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

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

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

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: 1) average years of schooling; 2) the share of workers with high-school degrees; 3) the share of cognitive workers; 4) the share of production workers; 5) average workers' age; 6) firm employment size; and 7) firm employment percentiles (divided into 10 bins) within each industry-year bin. 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 A.6: Wage Profiles and Firm Characteristics (Controlling for Tenure)

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

Note: This table presents estimates from regressions of firm-year-level returns to 20 years of experience on firm characteristics. Senior workers refer to workers in experience bins of 31–40 years, whereas young workers refer to workers in experience bins of 1–20 years. The baseline group is non-exporters. The controls are: 1) average years of schooling; 2) the share of workers with high-school degrees; 3) the share of cognitive workers; 4) the share of production workers; 5) average workers' age; 6) firm employment size; and 7) firm employment percentiles (divided into 10 bins) within each industry-year bin. Robust standard errors are in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

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

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

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. Because unit prices are not directly comparable across products, we first compute firms' unit prices of products relative to average unit prices of exports to Argentina (which is of similar development levels to Brazil) for each 8-digit product and year. We then use export volume as weights to compute a weighted average unit price of exports for each firm and year. The controls are: 1) average years of schooling; 2) the share of workers with high-school degrees; 3) the share of cognitive workers; 4) the share of production workers; 5) average workers' age; 6) firm employment size; and 7) firm employment percentiles (divided into 10 bins) within each industry-year bin. Robust standard errors are in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Table A.8: Wage Profiles and Firm Characteristics

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

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: 1) average years of schooling; 2) the share of workers with high-school degrees; 3) the share of cognitive workers; 4) the share of production workers; 5) average workers' age; 6) firm employment size; and 7) firm employment percentiles (divided into 10 bins) within each industry-year bin. Robust standard errors are in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Table A.9: Wage Profiles and Control Variables

	Dep Var: Firm-year-level Returns to 20 Yrs of Experience									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Sample period	94–10	94–10	94–10	94–10	94–10	94–10	94–10	94–10	94–10	94–10
Exporter	-0.015	-0.013	-0.015	-0.015	-0.016	-0.015	-0.056	-0.012	-0.027	-0.036
	(0.035)	(0.033)	(0.033)	(0.034)	(0.033)	(0.035)	(0.076)	(0.034)	(0.041)	(0.044)
Exporter ×	0.134***	0.128**	0.139***	0.136***	0.134***	0.135***	0.189*	0.139***	0.170**	0.119*
ratio of #high-income to #total dests	(0.052)	(0.052)	(0.052)	(0.053)	(0.053)	(0.053)	(0.111)	(0.053)	(0.071)	(0.064)
Average years of schooling ×		0.021								
ratio of #high-income to #total dests		(0.022)								
Share of high-school graduates ×			-0.098							
ratio of #high-income to #total dests			(0.200)							
Average workers' age × ratio of				-0.011						
#high-income to #total dests				(0.016)						
Share of production workers × ratio of					-0.108					
#high-income to #total dests					(0.228)					
Share of managers × ratio of						-0.113				
#high-income to #total dests						(0.670)				
Share of marketing workers × ratio of							0.302			
#high-income to #total dests							(0.550)			
Share of cognitive workers × ratio of								-0.038		
#high-income to #total dests								(0.266)		
Log firm employment × ratio of									-0.045	
#high-income to #total dests									(0.042)	
Firm employment percentile (0–10%) ×										0.616
ratio of #high-income to #total dests										(0.750)
Firm employment percentile (10–20%) ×										-0.292
ratio of #high-income to #total dests										(0.729)
Firm employment percentile (20–30%) ×										-0.213
ratio of #high-income to #total dests										(0.427)
Firm employment percentile (30–40%) ×										-0.450
ratio of #high-income to #total dests										(0.318)
Firm employment percentile (40–50%) ×										-0.301
ratio of #high-income to #total dests										(0.264)
Firm employment percentile (50–60%) ×										0.127
ratio of #high-income to #total dests										(0.224)
Firm employment percentile (60–70%) ×										-0.125
ratio of #high-income to #total dests										(0.169)
Firm employment percentile (70–80%) ×										0.146
ratio of #high-income to #total dests										(0.140)
Firm employment percentile (80–90%) ×										0.074
ratio of #high-income to #total dests										(0.105)
Industry and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	344,658	344,658	344,658	344,658	344,658	344,658	344,658	344,658	344,658	344,658
R-squared	0.319	0.319	0.319	0.319	0.319	0.319	0.319	0.319	0.319	0.319

Note: This table presents estimates from regressions of firm-year-level returns to 20 years of experience on firm characteristics. The controls are: 1) average years of schooling; 2) the share of workers with high-school degrees; 3) the share of cognitive workers; 4) the share of production workers; 5) average workers' age; 6) firm employment size; and 7) firm employment percentiles (divided into 10 bins) within each industry-year bin. Due to the space constraint, we do not report the coefficient on the interaction between the control variable and the exporter dummy, which is statistically insignificant in all scenarios. We also control for the levels of control variables when the corresponding interaction term is included. The baseline group is non-exporters in the upper 10% of firm employment distribution within each industry-year. Robust standard errors are in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

Table A.10: Difference in Observables in the Pre-exporting Period before Entry into High-income Destinations

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

Table A.11: 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	0.038	-0.144	0.080
	(0.120)	(0.103)	(0.103)
Nr treated	1,460	1,545	1,410
Nr controls	105,627	92,405	73,777
(b) Outcome: growth in returns (relative to $\tau = -1$ period)			
Export entry	0.000	-0.003	-0.175
	(0.167)	(0.159)	(0.162)

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

Table A.12: 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	0.078	-0.018	-0.016	0.014
	(0.078)	(0.099)	(0.106)	(0.110)
Nr treated	4,608	2,619	2,061	1,757
Nr controls	131,248	98,959	76,805	60,459
(b) Outcome: growth in returns (relative to $\tau = -1$ period)				
Export entry	0.060	-0.029	0.009	-0.113
	(0.112)	(0.142)	(0.159)	(0.163)

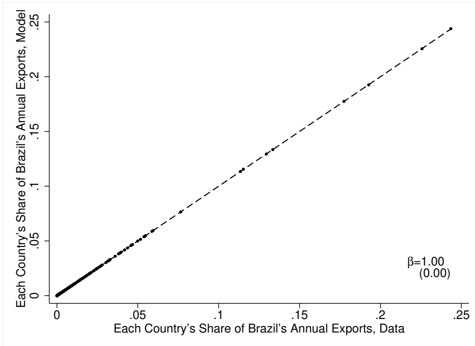
Notes: The table reports the difference of returns to experience and growth in returns (relative to $\tau = -1$ period) between new exporters and non-exporters. The propensity score is estimated based on a Probit model, including a host of pre-exporting (previous year) firm characteristics: 1) average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

Table A.13: Identification of Parameters γ_1 and γ_2

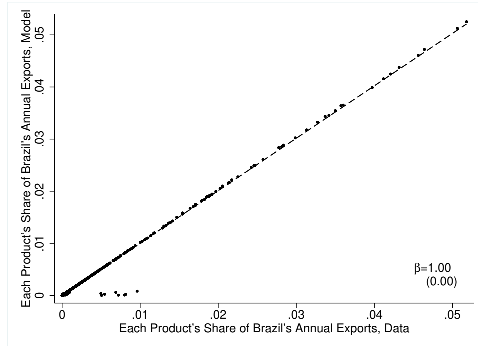
	Slope of Experience Returns on Firm Size	ΔExperience Returns (after entry into high-income dests)
Elasticity w.r.t γ_1	1.20	0.06
Elasticity w.r.t γ_2	0.49	4.81

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

Figure A.1: Check of Customs Data with Official Reported Data, 97–00



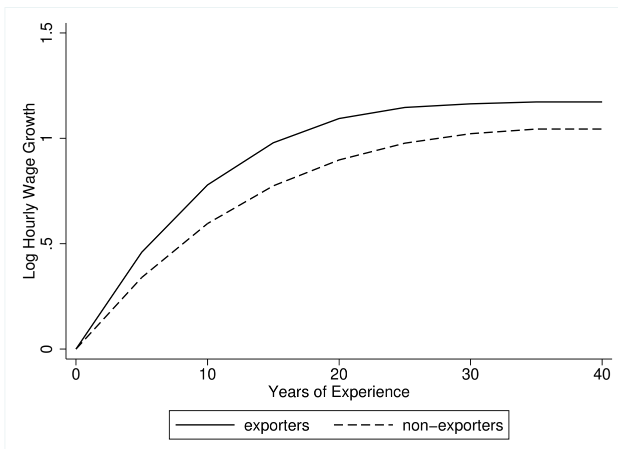
(a) Exports by Country



(b) Exports by 8-digit Products

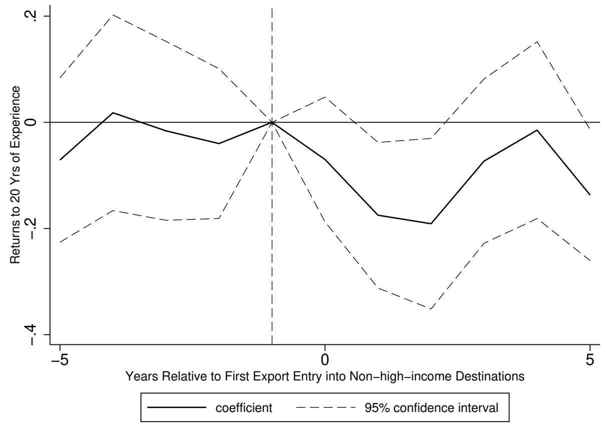
Note: This graph compares each country's (product's) share of Brazilian annual exports between our customs data and the officially reported data from the Brazilian Ministry of Economy (Ministério da Economia). We pool the different years' shares together in the graph.

Figure A.2: Log Hourly Wage Increase by Exporters and Non-exporters



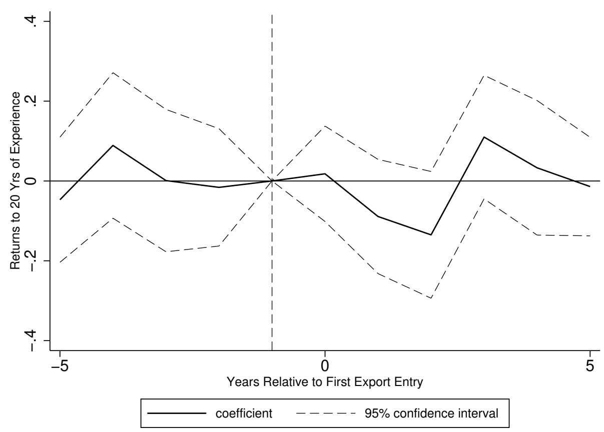
Note: This figure presents the experience-wage profiles for workers at exporters and non-exporters, from estimating equation (1) using the Brazilian data between 1994–2010. We assume the final 5 years with no experience returns.

Figure A.3: Dynamics of Firms' First Entry Into Non-high-income Destinations



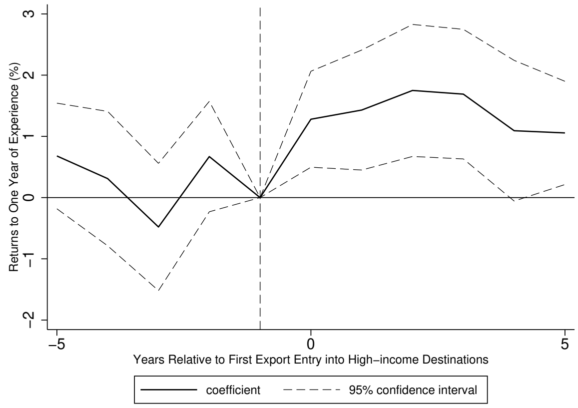
Note: The figure shows the β_τ parameters from estimating equation (4), except for that the β_τ parameters are coefficients on indicators for time periods relative to the firm's first export entry into non-high-income destinations. The dependent variable is firm-year-level returns to 20 years of experience. The regression controls for firm fixed effects, industry fixed effects, year fixed effects, and a dummy variable indicating whether the firm is exporting to a high-income destination. The other controls are: 1) average years of schooling; 2) the share of workers with high-school degrees; 3) the share of cognitive workers; 4) the share of production workers; 5) average workers' age; 6) firm employment size; and 7) firm employment percentiles (divided into 10 bins) within each industry-year bin. To estimate the β_τ parameters after entry, we require that firms remain exporting to non-high-income destinations.

Figure A.4: Dynamics of Firms' First Export Entry

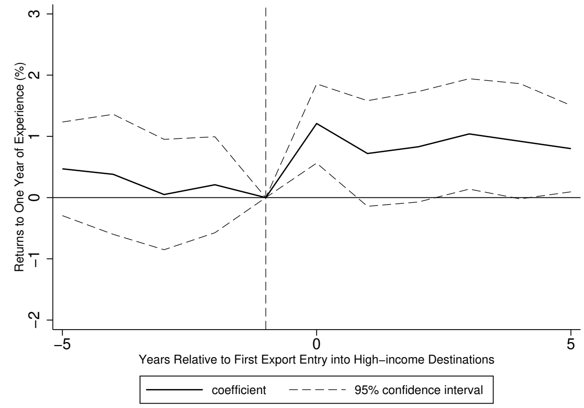


Note: The figure shows the β_τ parameters from estimating equation (4), except for that the β_τ parameters are coefficients on indicators for time periods relative to the firm's first export entry. The dependent variable is firm-year-level returns to 20 years of experience. The regression controls for firm fixed effects, industry fixed effects, and year fixed effects. The other controls are: 1) average years of schooling; 2) the share of workers with high-school degrees; 3) the share of cognitive workers; 4) the share of production workers; 5) average workers' age; 6) firm employment size; and 7) firm employment percentiles (divided into 10 bins) within each industry-year bin. To estimate the β_τ parameters after entry, we require that firms remain exporting.

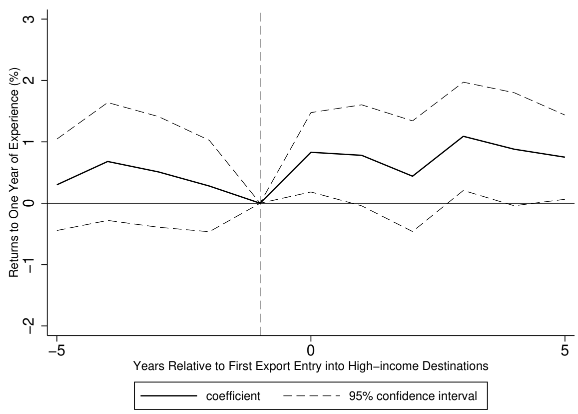
Figure A.5: Returns to One Year of Experience Across Different Experience Bins



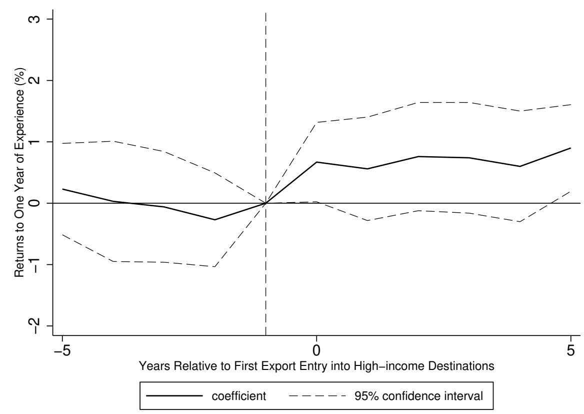
(a) Workers with 1–5 Years of Experience



(b) Workers with 6–10 Years of Experience



(c) Workers with 10–15 Years of Experience



(d) Workers with 16–20 Years of Experience

Note: The figure shows the β_τ parameters from estimating equation (4). The dependent variable is firm-year-level returns to one year of experience in the corresponding experience bin. The regression controls for firm fixed effects, industry fixed effects, year fixed effects, and a dummy variable indicating whether the firm is exporting to a non-high-income destination. The other controls are: 1) average years of schooling; 2) the share of workers with high-school degrees; 3) the share of cognitive workers; 4) the share of production workers; 5) average workers' age; 6) firm employment size; and 7) firm employment percentiles (divided into 10 bins) within each industry-year bin. To estimate the β_τ parameters after entry, we require that firms remain exporting to high-income destinations.

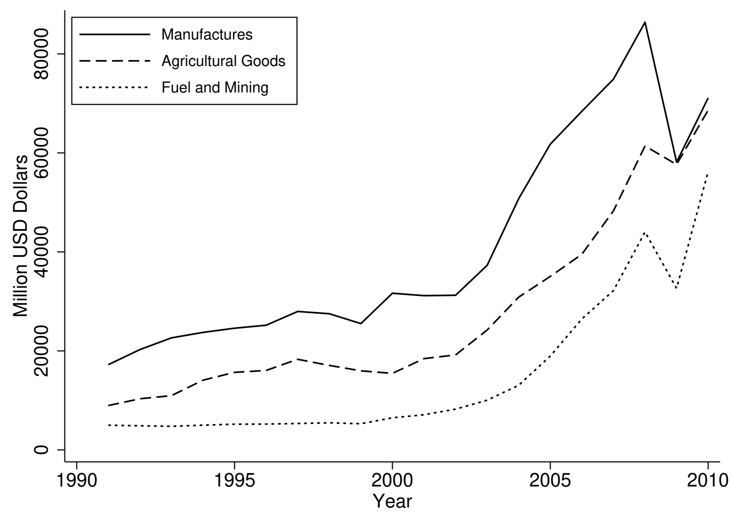
B The Brazilian Economy

B.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 B.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 B.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 B.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 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 B.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

Table B.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.

value of manufactured products also substantially increased.

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

Figure B.2a shows unregistered workers as a share of total employees. The informality rate sharply declined in recent decades, from around 33% in the 1990s to 23% in the 2010s. In Brazil's Population Census 2000 and 2010, we have information on the contract status of wage workers. We split the sample into wage workers with formal contracts and with no formal contracts. 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 B.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

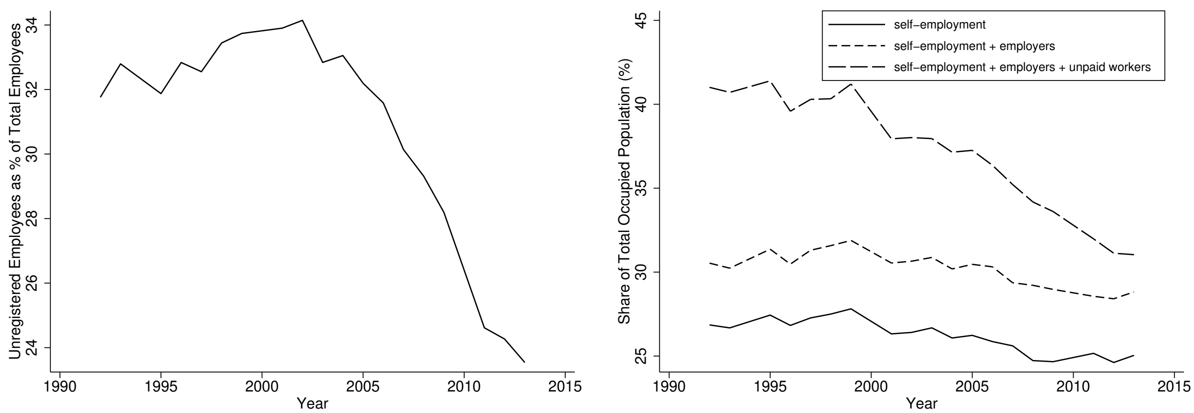
Table B.2: Exports by Products

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

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

may not appear in RAIS (except for employers who receive a wage). Figure B.2b shows the share of self-employed workers, employers and unpaid workers in Brazilian total employment. These three types of employment represented 30–40% of Brazilian employment in the 1990s and 2000s. We use 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 at the end of the working life and a 0% depreciation rate. As shown in Figure B.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



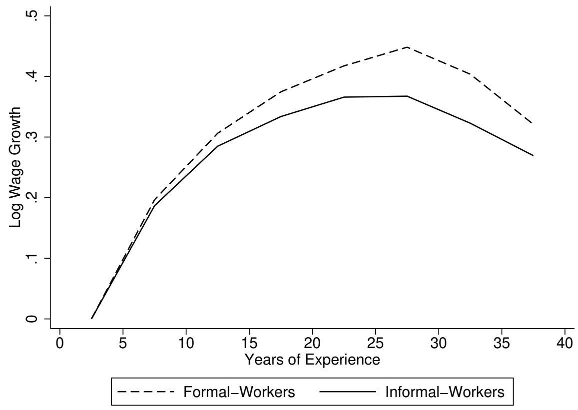
(a) Share of Informal Employees **(b)** Share of Non-employees in Occupied Pop

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.

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.

C Description of the RAIS and Customs Data

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



(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.

identification codes as firm IDs and rely on firm IDs to identify and track firms.

Firms are mandated by law to annually provide workers' information to RAIS, and thus the data 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 (8-digit identification codes) to merge the RAIS data with Brazilian customs declarations for merchandise exports collected at SECEX (Secretaria de Comércio Exterior) for the years 1994–2010.[56] Thus, we use RAIS merged with customs data for

[56]Using firms' identification codes to merge the RAIS data with customs data is a common practice in

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.

C.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-schooling}). In each year, we obtain experience-wage profiles by computing the average log hourly wage for workers in each 5-year experience bin $x \in X = \{1\text{–}5, 6\text{–}10, \ldots, 36\text{–}40\}$, 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 C.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 0.73 (0.50) higher than workers with 1–5 years of experience.[57] This pattern holds in different time periods (Columns (2)–(3)) and after controlling for industry composition in Column (4). More notably, it is not caused by lower starting wages of workers at exporters. In the last two columns of Panel A, we recompute the average log wage of each experience bin relative to workers with 1–5 years of experience at non-exporters for any given year. We find that workers with 1–5 years of experience already have higher wages at exporters than at non-exporters. This gap grows larger as workers' experience increases.

In light of potential composition effects (exporters are larger and have a better workforce), in Panels B to D of Table C.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),[58] 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. We formally estimate experience-wage profiles in Section 2.2.

the literature studying the Brazilian trade activities (e.g., Aguayo-Tellez et al. 2010, Helpman et al. 2017, Dix-Carneiro et al. 2019).

[57] 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)).

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

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

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

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 (5)–(6) of Panel A use the average log wage of workers with 1–5 years of experience at non-exporters as normalization. In Column (4) of Panel A, we control for industry composition by first computing experience-wage profiles for workers at exporters and non-exporters in each industry, respectively. Then, we use the aggregate employment in each industry (aggregated over exporters and non-exporters) as weights to compute experience-wage profiles for workers at exporters and non-exporters, respectively.

D Empirical Method

D.1 HLT Method

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

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

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

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

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

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

$$\Delta \log(w_{i,t}) = \sum_{x \in X} \phi^x_s D^x_{i,t} + g_s + (e_{s,t} - e_{s,t-1}) + \epsilon_{i,t}. \tag{D.3}$$

We then restrict cyclical components to average zero over the time period $\sum_t e_{s,t} = 0$ and to be orthogonal to a time trend $\sum_t e_{s,t} t = 0$. These two restrictions reduce the freedom of $\{e_{s,t}\}$ by two and resolve the collinearity problem of time and experience returns ($e_{s,t}$ and $\sum_x D^x_{i,t}$), 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, $\phi^{31-35}_s + \phi^{36-40}_s = 0$.

In short, the first method transforms time effects $\{\gamma_{s,t}\}$ into trends $\{\zeta_{s,t}\}$, which naturally reduces the freedom of parameters by one, and then introduces one additional restriction $\phi^{31-35}_s + \phi^{36-40}_s = 0$ 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 $\phi^{31-35}_s + \phi^{36-40}_s = 0$ to pin down. Empirically, we find that these two different ways of dealing with time effects lead to very similar results.

D.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:

$$E(y^1_\omega - y^0_\omega | D_\omega = 1) = E(y^1_\omega | D_\omega = 1) - E(y^0_\omega | D_\omega = 1). \tag{D.4}$$

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

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

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,

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

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).

E Additional Empirical Results

E.1 Industry Composition and Returns to Experience

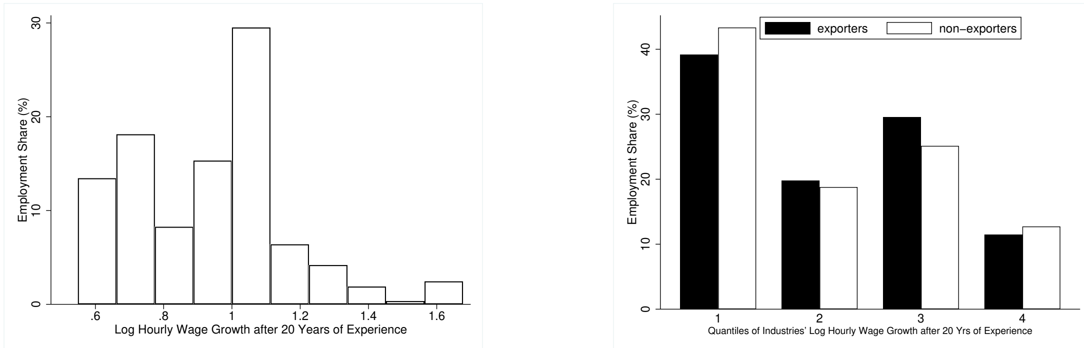
This difference in experience-wage profiles between exporters and non-exporters can be explained by different reasons. One important driver of the result can be industry composition. This is motivated by two well-established results in the literature: (1) different industries have different returns to experience (e.g., Dix-Carneiro 2014, Islam et al. 2018); and (2) trade induces industry specialization and labor reallocation, possibly driven by comparative advantage (e.g., Costinot et al. 2012) or home market effects (e.g., Head and Ries 2001). Therefore, if exporters are more concentrated in industries with higher returns to experience than non-exporters, exporters will on average also have steeper experience-wage profiles.

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

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

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

Figure E.1: Returns to Experience and Industry Heterogeneity



(a) Distribution of Log Hourly Wage Increase Across Industries

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

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

with higher returns to experience, trade openness can lead to higher earnings growth. On the other hand, for other countries, trade openness can generate lower earnings growth by allocating workers toward industries with lower returns to experience.

Second, in Brazil, industry composition is not important for the aggregate difference in returns to experience between exporters and non-exporters. Using industry-specific returns to experience and different employment distributions across industries for exporters and non-exporters, we find that after 20 years of experience, workers' wage increase would be 1 percentage point higher at exporters than at non-exporters due to industry composition.

E.2 Case Study: Brazilian Currency Crisis

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

In January and February 1999, Brazil experienced a massive devaluation of its domestic currency, with the Brazilian Real per U.S. dollar increasing from 1.20 in December 1998 to 1.93 in February 1999, a 60% devaluation within two months.[59] The abrupt currency devaluation was detrimental to the economy in many ways, but nonetheless it improved Brazilian firms' competitiveness in the global market and induced more firms to export. In Figure E.2b, we show that the probability of firms exporting strongly increased after 1999 (relative to year 1998, after controlling for firm fixed effects and industry fixed effects), while

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

there was no effect in the year prior to the large devaluation episode and a small increase in the previous years. Similarly, Verhoogen (2008) finds that the Mexican peso crisis in 1994 led to more firms' entry into exporting, and Macis and Schivardi (2016) finds the 1992 devaluation of the Italian lira also led to higher export shares of sales.

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

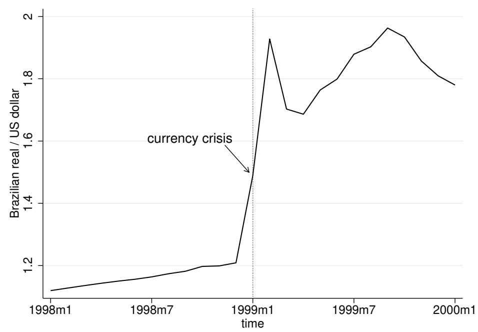
$$\begin{aligned} y_{\omega,t} =&\beta_0 + \beta_1 Exporter_{\omega,t} \times DV + \beta_2 Exporter_{\omega,PRE} \times DV + \beta_3 Exporter_{\omega,t} \times (1 - DV) \\ &+ \gamma_1 Ratio\_high_{\omega,t} \times DV + \gamma_2 Ratio\_high_{\omega,PRE} \times DV + \gamma_3 Ratio\_high_{\omega,t} \times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

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

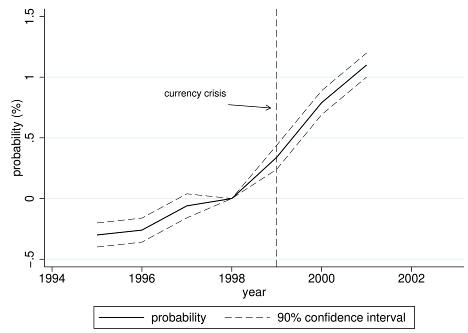
In this DID design, we impose two implicit assumptions for identification: (1) most changes in firms' export status after 1999 were due to improved competitiveness with currency devaluation; and (2) this currency devaluation affected returns to experience through changes in export activities, but was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

Table E.1 presents the results. Regardless of the chosen time frame, the results show that the interaction between exposure to high-income destinations and the devaluation dummy is always significantly positive. This indicates that entry into high-income destinations induced by the currency devaluation increased returns to experience.

Figure E.2: Brazil Currency Crisis and Exporting Probability



(a) Brazil Currency Crisis



(b) Exporting Probability

Note: Panel (a) presents the monthly Brazilian nominal exchange rates (per U.S. dollar), which are drawn from https://fxtop.com/. Panel (b) presents the probability of a firm exporting in each year. To obtain the probability, we regress the dummy variable of the export status (1, if the firm exports, and otherwise 0) on firm fixed effects, industry fixed effects, and year fixed effects. We plot the coefficients on year effects relative to 1998 (the baseline year) in Panel (b).

E.3 Panel Estimation of Workers' Experience Effects

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

$$\log w_{i,k,t} = \theta_k Eduyrs_{i,t} + \sum_{x \in X} \sum_{k' \in \{e,n\}} \phi^x_{k'} Exp^x_{i,k'} + \mu_i + \theta_{\omega(i,t)} + \delta_{k,t} + \epsilon_{i,k,t}, \tag{E.2}$$

where i, ω, k and t represent individual, firm, firm export status, and time, respectively. $w_{i,k,t}$ is the hourly wage for an individual i currently working in firms of export status $k \in \{e, n\}$, either exporters (e) or non-exporters (n). The variable $Eduyrs_{i,t}$ represents schooling, of which the returns can depend on the current firm type. The variable $Exp^x_{i,k'}$ denotes her accumulated years of experience in type-k' firms ($k' \in \{e, n\}$) in each experience bin x of her work history (before current year). $\phi^x_{k'}$ refers to the effect of a one-year increase in experience $Exp^x_{i,k'}$ on current wages. We let $\phi^x_{k'}$ differ across experience bins to capture that experience returns vary across different stages of life: For example, one year of experience accumulated just after entry of the labor market could have different effects compared with one year of experience accumulated in a later life stage. μ_i is a vector of individual fixed effects; $\theta_{\omega(i,t)}$ is the fixed effect of the firm hiring worker i in time t; and $\delta_{k,t}$ is a vector of time effects specific to firm export status. We also control for industry effects and firm-year-level workforce characteristics as in Table 2 (for the firm currently hiring the worker), which are not specified in the equation to save notation.

To proceed with estimation of our regression in equation (E.2), 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

Table E.1: Dep Var: Firm-year-level Log Hourly Wage Increase (20 Years of Experience)

time	(1) 1998-2000	(2) 1997-2001	(3) 1996-2002
Exporter × DV	-0.024	-0.115	-0.090
	(0.130)	(0.090)	(0.071)
Exporter$_{PRE}$ × DV	1.416*	0.194	0.089
	(0.845)	(0.587)	(0.483)
Exporter × (1-DV)	0.240	-0.023	0.058
	(0.196)	(0.121)	(0.090)
Ratio of #high-income dests to #total dests × DV	0.417**	0.313**	0.276**
	(0.194)	(0.138)	(0.110)
Ratio of #high-income dests to #total dests$_{PRE}$ × DV	-1.079	0.262	0.530
	(1.559)	(1.086)	(0.874)
Ratio of #high-income dests to #total dests × (1-DV)	0.082	0.265	0.144
	(0.316)	(0.202)	(0.146)
Year, industry and firm FE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
Obs	59,721	100,393	142,278
R-squared	0.604	0.486	0.412

Note: This table presents estimates from equation (E.1). The dependent variable is firm-year-level returns to 20 years of experience. The regression includes firm, industry, and year fixed effects. The controls are: 1) average years of schooling; 2) the share of workers with high-school degrees; 3) the share of cognitive workers; 4) the share of production workers; 5) average workers' age; 6) firm employment size; and 7) firm employment percentiles (divided into 10 bins) within each industry-year bin. Robust standard errors are in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

on workers that first appeared in the database within 5 years after finishing schooling[60] 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' wages to be within a job, we can explore how experience affects wages after workers switch firms.

Column (1) of Table E.2 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

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

changes in schooling over time (subject to large noises). Instead, a cross-sectional Mincer regression indicates that the return to education is 8.6% per year of schooling, in close accord with the literature (e.g., Young 2013). More importantly, according to our estimation results, if a new worker with average schooling (9 years) starts her job at exporters, she enjoys a $-0.018 + 0.003 \times 9 = 0.9\%$ wage premium relative to a job at non-exporters. If she continues to work at exporters, her wage growth is 15 percentage points higher than working at non-exporters over 20 years of experience, in line with our estimation results in Section 2.2.

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

In Column (3) of Table E.2, 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 (E.2), in order to explore the destination-specific effects. According to the results, we find that if a worker accumulates 20 years of experience at exporters from the beginning of the career, working at exporters that only export to high-income destinations would lead to a 7% higher wage than working at exporters that only export to non-high-income destinations. This result is in similar magnitude to our firm-level results in Table 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 a 12% higher post-displacement wage than previously working at exporters that only export to non-high-income destinations.

Table E.2: Dependent Variable: Log Hourly Wage (Current Year)

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

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). We also control for industry effects and firm-year-level workforce characteristics (for the firm hiring the worker): 1) average years of schooling; 2) the share of workers with high-school degrees; 3) the share of cognitive workers; 4) the share of production workers; 5) average workers' age; 6) firm employment size; and 7) firm employment percentiles (divided into 10 bins) within each industry-year bin. Robust standard errors are in parentheses. Significance levels: * 10%, ** 5%, *** 1%.

F Additional Theoretical Results

F.1 Proof of Proposition 1

F.1.1 Optimal Quantities Sold to Export Destinations

Because the discount rate ρ is large enough, the choice of export destinations does not rely on the future job value. We first solve the optimal quantities $\{y_n(\omega)\}$ given the export decisions $\{I_n(\omega)\}$. According to equation (15), now the problem becomes:

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

We can redefine the problem as:

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

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

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

Solving these first-order conditions leads to:

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

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

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

F.1.2 Optimal Hires and Export Choices

Because unemployment benefits $V_U^a(h_i^a) = 0\ \forall\ i, a$ and the discount rate ρ is large enough, firms obtain a fixed portion $(1-\beta)$ of total sales according to equation (13). According to equation (16):

$$(1-\beta)\frac{\sum_n I_n(\omega)y_n(\omega)^{\frac{\sigma-1}{\sigma}}P_nY_n^{\frac{1}{\sigma}}}{h(\omega)}\frac{A}{V}\bar{h}=c_vP_1.$$

where $\frac{A}{V}$ is the number of hires per vacancy (recall A is the total population), and $\bar{h}$ is the average human capital of workers in the economy. Noting that $h(\omega)=\frac{v(\omega)}{V}A\bar{h}$. Combining this with equation (F.3) yields the optimal $v(\omega)$,

$$v(\omega)=(1-\beta)^{\sigma}\left(\sum_{n=1}^{N}I_n(\omega)P_n^{\sigma}Y_n\tau_n^{1-\sigma}\right)\left(\frac{z(\omega)A\bar{h}}{V}\right)^{\sigma-1}(c_vP_1)^{-\sigma}. \tag{F.5}$$

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

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

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

$$p_n(\omega)=\frac{\tau_nc_vP_1V}{(1-\beta)z(\omega)A\bar{h}}, \tag{F.7}$$

which resembles a Melitz-Chaney-type model with prices of production $\frac{c_vP_1V}{(1-\beta)A\bar{h}}$ if $z(\omega)=1$. Because workers capture a portion β of firms' revenue, workers' average wage at firm z is

$$\bar{w}_1=\bar{w}_1(\omega)=\beta\bar{h}\frac{\sum_n I_n(z)p_n(\omega)y_n(\omega)}{h(\omega)}=\frac{\beta c_vP_1V}{(1-\beta)A}, \tag{F.8}$$

which is identical across firms.

As shown in equation (F.6), 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 $p_n(\omega)y_n(\omega)\geq f_nP_1$.

F.1.3 Trade Shares in the Home Market

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

$$\begin{aligned}\Pi_d&=\frac{\bar{M}\int_{z_{\min}}^{\infty}p_1(\omega)^{1-\sigma}d\Phi(z(\omega))}{\bar{M}\int_{z_{\min}}^{\infty}p_1(\omega)^{1-\sigma}d\Phi(z(\omega))+\bar{M}^I(p^I)^{1-\sigma}}\\&=\frac{\bar{M}\int_{z_{\min}}^{\infty}z(\omega)^{\sigma-1}d\Phi(z(\omega))\left(\frac{c_vP_1V}{(1-\beta)A\bar{h}}\right)^{1-\sigma}}{\bar{M}\int_{z_{\min}}^{\infty}z(\omega)^{\sigma-1}d\Phi(z(\omega))\left(\frac{c_vP_1V}{(1-\beta)A\bar{h}}\right)^{1-\sigma}+\bar{M}^I(p^I)^{1-\sigma}},\end{aligned} \tag{F.9}$$

where we use equation (F.7). Note this is a standard gravity equation with trade elasticity $\sigma - 1$, as typically used in the trade literature (reviewed by Costinot and Rodríguez-Clare 2014). And the price index in the home country is

$$P_1 = \left(\bar{M} \int_{z^*_{\min}}^{\infty} z(\omega)^{\sigma-1} d\Phi(z(\omega)) \left(\frac{c_v P_1 V}{(1-\beta)A\bar{h}} \right)^{1-\sigma} + \bar{M}^I (p^I)^{1-\sigma} \right)^{\frac{1}{1-\sigma}}. \tag{F.10}$$

F.1.4 Gains from Trade

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

$$X_1 = \frac{A\bar{w}_1}{\beta P_1} = A(\Pi_d)^{-\frac{1}{\sigma-1}} \bar{h} \left(\bar{M} \int_{z^*_{\min}}^{\infty} z(\omega)^{\sigma-1} d\Phi(z(\omega)) \right)^{\frac{1}{\sigma-1}} \tag{F.11}$$

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

$$GT = \underbrace{\Pi_d^{-\frac{1}{\sigma-1}}}_{\text{changes in real income per efficiency labor}} \times \underbrace{\frac{\bar{h}}{\bar{h}^{aut}}}_{\text{changes in average efficiency labor per employee}}. \tag{F.12}$$

This completes the proof.

F.2 Incorporating Learning-by-doing into Model

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 that for a worker of age a at firm ω, the human capital growth is exogenously given by:

$$\phi^{E,a}(\omega) = \mu z(\omega)^{\gamma_1} \phi^O(\omega)^{\gamma_2} \exp(-\rho_h a). \tag{F.13}$$

Compared with our baseline model, we now assume: 1) there is no time needed for human capital accumulation, and this implies that the time spent on human capital accumulation $s^a = 0$; and 2) to generate a reduction in learning speed in later ages, we introduce an additional parameter $\rho_h > 0$. We calibrate the newly introduced $\rho_h > 0$ together with other parameters (which are same as in the baseline model) to match the targeted moments. 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. The other targeted moments are the same as in Table 6. We find $\gamma_1 = 0.57$ and $\gamma_2 = 0.55$ in this learning-by-doing model.

G Additional Quantitative Results

G.1 Computation Algorithm

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

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

2. We then draw the random realization of export fixed costs for each firm and each destination. The realizations of export costs are fixed in the baseline equilibrium throughout the paper. We also experimented with 50 different realizations for each firm and destination and then use the average simulation results to compute the model moments, and the results are very similar (though computationally cumbersome).

3. Given a set of parameters, we compute the baseline equilibrium. To compute moments regarding changes immediately following export entry, we implement a different realization of export fixed costs for each firm on the baseline equilibrium. As it is difficult to compute the full transitional dynamics, we focus on the immediate period of export entry with firms' employment distribution and aggregate variables being the same as in the baseline equilibrium. We compute how the changes (due to export entry) in labor productivity and the human capital increment per time spent affect experience effects. This is motivated by our estimated effects in Table 3 that capture the short-run effects.[61] 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.

G.2 Role of Labor Market Frictions

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

[61] 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.

Table G.1: Gains in Human Capital from Trade with Alternative Labor Market Frictions

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

In Table G.1, we find that in the exercise with full employment (job finding rate $\lambda_U = 1$), the gains in human capital from trade decline compared with the baseline results. This is mainly due to that in the baseline model, trade openness encourages more job vacancies and reduces duration of unemployment, which also facilitates human capital formation (unemployed workers do not accumulate human capital on the job), and this channel is missing in the model with full employment. With job separation rate $\kappa = 1$, the gains in human capital from trade also decline compared with the baseline results. Here, the lower gains are partly driven by the reduced concentration of employment in more productive firms due to the absence of job-to-job transitions,[62] which disfavors human capital formation as more productive firms also provide more learning opportunities. Finally, if we set both job finding rate $\lambda_U = 1$ and job destruction rate $\kappa = 1$, due to the combined effects, the decline in the gains in human capital becomes even larger compared with separately setting $\lambda_U = 1$ or $\kappa = 1$.

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