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

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Abstract

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1 Introduction

Differences in life-cycle wage growth between firms are well documented (Herkenhoff et al., 2018; Gregory, 2021; Jarosch, Oberfield and Rossi-Hansberg, 2021), and so are differences in wages between exporters and non-exporters (Bernard and Jensen, 1995). Yet little is known about the effects of firms' export activity on workers' life-cycle wage dynamics. 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, Lach and Tybout, 1998), but there can also be productivity improvements after exporting. For example, Atkin, Khandelwal and Osman (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. In addition to changing firm-level outcomes, exporting may impact workers.

We study empirically the relationship between a firm's export-market participation and its workers' wage profiles. We rely on Brazilian employer-employee data and customs records between 1994–2010 in the manufacturing sector, 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 at different life cycle stages. In principle, both one more year of experience and a change in aggregate time effects can lead to a wage change. To resolve this well-known collinearity problem (Deaton, 1997), we draw upon the widely used Heckman–Lochner–Taber approach (Heckman, Lochner and Taber 1998, henceforth HLT, also applied in, e.g., Huggett, Ventura and Yaron 2011; Lagakos et al. 2018). The centerpiece of this approach is to assume that there are no experience returns at the end of the working life, so that wage growth among old workers 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 life-cycle 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, hinting that exporters essentially provide higher returns to experience. Third, after controlling for productivity proxies, workforce 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 a firm's entry into a high-income destination, and this result is robust when we apply a propensity-score matching approach or exploit a substantive currency devaluation to address the endogeneity concern of export decisions.

We show that our empirical results are robust to using a subsample of workers who are observed in the data from young age on and for whom we can construct experience based on the observed work history. Because of possible breaks in the observed employment records (for reasons such as unemployment), which resolve the collinearity between experience and time, we do not need to impose the HLT assumption in estimation for this subsample. We still find that previous experience at exporters (especially at those selling to high-income markets) is more valuable than experience at non-exporters, and that these experience gains are largely portable when workers switch firms. The estimated experience effects are of a similar magnitude to our previous findings. We also show similar results for workers displaced under a sudden closure of large firms. These displaced workers' returns to previous experience are more likely to be shaped by learning than seniority (Jacobson, LaLonde and Sullivan, 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 body of quantitative research studying earnings components (e.g., Rubinstein and Weiss, 2006; Burdett, Carrillo-Tudela and Coles, 2011; Bagger et al., 2014; Helpman et al., 2017; Gregory, 2021). The second contribution of this paper is to develop and quantify a dynamic model of multi-worker firms with export market entry, worker-firm wage bargaining, and human capital accumulation to interpret the data and conduct experiments.

Our model builds on the framework by Cahuc, Postel-Vinay and Robin (2006, henceforth

CPR), where firms meet workers by random search. When matched, workers and firms negotiate the contractual piece rate (the portion of revenues paid to the worker), and workers and firms renegotiate the piece rate when workers are being poached. 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 accumulation per time increases with firm productivity and with the sales-weighted average knowledge about firms' markets.[1] Staying at highly productive firms (which tend to select into exporting) and being exposed to destinations with abundant knowledge can therefore generate faster human capital growth. Second, we consider destinations to be heterogeneous in their knowledge stocks so that different combinations of destinations lead to varying 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 the relative contributions, we calibrate our model to the Brazilian manufacturing sector and target relevant moments to discipline the importance of wage bargaining and human capital investment. In the calibrated model, human capital growth can explain 70% of the overall within-job wage profiles. Human capital growth accounts for 50% of the differences in wage profiles between exporters and non-exporters and, among exporters, between the exporters that ship to high-income destinations and those that do not. Diminishing returns to human capital investment mitigate the learning effect. Our calibrated model also matches 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 labor efficiency due to trade openness. We then perform a decomposition of the trade-induced increase in workers' human capital. Consistent with our empirical evidence, the labor efficiency increase is mostly driven by increased knowledge after firms' entry into high-income destinations. To understand the impact

[1] Monge-Naranjo (2019) and Engbom (2022) also model the dependence of learning returns on firm productivity but do not consider the possibility that human capital gains may vary by the firm's product markets.

of further trade liberalization, we lower trade costs from Brazil to specific export destinations. We find that the gains in real income depend on the knowledge stocks at the destinations and that there can be real-income losses. 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' human capital. In contrast, 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' human capital as firms enter product markets with low knowledge stocks.

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, Roberts and Xu, 2011; De Loecker, 2013; Atkin, Khandelwal and Osman, 2017). Artopoulos, Friel and Hallak (2013) provide case studies in Argentina, showing that export pioneers learn to adopt new practices for foreign markets. Studies also explore how portable knowledge from trade benefits workers and firms, including how firms' import and export choices are related to employees' experience and earnings (Mion and Opromolla, 2014; Muendler and Rauch, 2018; Labanca, Molina and Muendler, 2021). Complementing those studies, we look into how export activity affects workers' wage growth within the firm over time. Our results indicate that exporting may enhance workers' human capital, especially with the exposure to advanced export destinations, and raise earnings.

In studying the earnings evolution, our paper also makes contact with research on life-cycle wage growth. The literature has proposed many factors affecting a worker's earnings over time, including aspects of job search (Bagger et al., 2014) and industry composition (Dix-Carneiro, 2014). There are few studies exploring the role of export participation in life-cycle wage growth. Mion and Ottaviano (2020) find higher wage profiles at internationally active firms than at domestic firms. Our paper explores in addition the relationship between types of export destinations and workers' wage profiles, and we develop a structural model to quantify the aggregate implications. By emphasizing how export destinations affect wage growth through human capital formation, our paper relates to a broad literature on the determinants of on-the-job human capital accumulation (e.g., Manuelli and Seshadri, 2014; De la Croix, Doepke and Mokyr, 2018). We show that the exporter wage premium over non-exporters increases with the workers' experience, which may partly reflect workers' faster human capital growth at exporters.

The substantive literature on firm-level export dynamics has largely abstracted from labor-market frictions. In a survey, Alessandria, Arkolakis and Ruhl (2021) point to two articles that combine firm dynamics and labor search: Cosar, Guner and Tybout (2016) and Fajgelbaum (2020). One additional publication is Felbermayr, Impullitti and Prat (2018), who show that convex adjustment costs generate a within-firm wage distribution because workers hired earlier in a firm's life cycle receive higher pay. A recent fourth contribution is Dix-Carneiro et al. (2021), introducing firm informality into the Cosar, Guner and Tybout (2016) model. Fajgelbaum (2020) most closely relates to our paper. Building on the CPR model of search and wage bargaining, as do we, Fajgelbaum (2020) studies the firms' forward looking employment decisions under labor market frictions and prospective export-market entry in the presence of job-to-job search. All four papers abstract from worker heterogeneity and human capital accumulation and cannot generate a wage-tenure profile. Our analysis focuses on the impact of export activity on workers' wage dynamics by age and accounts for workers' learning and life cycle choices.

Finally, we connect with a large literature on international knowledge diffusion (for a survey see Keller, 2021). Recent theoretical and quantitative papers explore the relation between trade-induced knowledge diffusion and firm productivity growth (e.g., Alvarez, Buera and Lucas, 2013; Perla, Tonetti and Waugh, 2015; Sampson, 2016; Buera and Oberfield, 2020), as reviewed by Lind and Ramondo (2019). That literature typically finds that trade accelerates 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 after introducing the diffusion of ideas between competitors. We highlight 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 the knowledge at export destinations.

The remainder of this paper is organized as follows. Section 2 describes our empirical findings and presents the interaction between wage profiles and destination markets. To understand the facts and perform quantitative analysis, Section 3 develops a firm-level model with export activity in a small open economy, wage bargaining, and human capital accumulation. Section 4 calibrates the model to match the data moments, and Section 5 performs several counterfactual exercises to study the role of trade openness for human capital formation and real income. Section 6 concludes.

2 Experience-Wage Profiles and Exporting

In this section, we present a set of stylized facts on the relationship between export activity and 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 first describe the data.

2.1 Data

We use the administrative matched employer–employee data RAIS (*Relação Anual de Informaçõs Sociais*) between 1994–2010.[2] RAIS offers a complete record of workers employed in the Brazilian formal sector. Firms are required by law to annually provide workers' information to RAIS and compliance results in the payment of one monthly minimum wage to workers (Menezes-Filho, Muendler and Ramey, 2008). Each record represents a worker-firm-year observation, containing worker ID, firm ID, and worker characteristics including schooling, age, hourly wage, occupation, and additional demographic information. One limitation of the data is the absence of the informal sector. Appendix A.2 discusses the characteristics of the Brazilian informal sector and shows that including informal workers may in fact strengthen our empirical results.

We restrict our empirical analysis to manufacturing firms. They produce tradable goods and have been studied extensively. We focus on full-time male workers aged between 18–65 and

[2]We describe the Brazilian economy and export patterns during our sample period in Appendix A.1.

employed at firms with at least 10 employees.[3] 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 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 at least one reported export transaction in that year. The SECEX data contains destinations and the 8-digit products that 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.[4]

Summary statistics are in Appendix B.1. In Appendix B.2, we use the raw data to present experience-wage profiles in the cross section of firms, showing that workers at exporters have steeper wage profiles than workers at non-exporters.[5] There are identification problems with this first-pass comparison, so we proceed to formally estimate experience-wage profiles.

2.2 Wage Profiles in the Aggregate and by Export Status

2.2.1 Constructing aggregate experience-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 the use of wage levels to estimate experience returns (Islam et al., 2019; Lagakos et al., 2018), this approach takes advantage of the panel structure of our employer-employee data—controlling for individual, firm,

[3]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 by female workers. According to the World Bank's estimates for those aged 15+ in Brazil, the female labor force participation rate increased from 45% in 1994 to 54% in 2010, whereas the male labor force participation rate was relatively stable, changing from 81% to 77% during the same period. The restriction by firm employment makes the sample comparable to that of other countries with similar truncations by size.

[4]Appendix Figure D.2 shows that between 1997–2000, each country's (product's) share of Brazilian annual exports from our customs data closely matches that in the official data from the Brazilian Ministry of the Economy.

[5]We also confirm typical patterns in the literature (Islam et al., 2019; Lagakos et al., 2018): more highly educated workers, workers at bigger firms, and workers in more sophisticated occupations have steeper wage profiles.

and match-specific fixed effects that affect wage levels while avoiding the incidental parameters issue (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:

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

where i and t represent individuals and years respectively. The subscript s is the level of aggregation for estimating experience returns (at exporters and non-exporters), which will be specified in later implementation. $\Delta \log(w_{i,t})$ denotes within-job wage growth, which is the log hourly wage growth from $t-1$ to t for individual i within the same firm.[6]

We cannot observe every worker's full employment history, so we follow Lagakos et al. (2018) and construct a measure of potential experience in the labor market as the minimum between age minus 18 and age minus 6 and the years of schooling, $\min\{$age-18,age-6-schooling$\}$. $D_{i,t}^x$ is a dummy variable that takes the value 1 if a worker's current potential experience is in experience bin $x \in \mathbb{X} = \{$1–5,6–10,...$\}$, where $\mathbb{X}$ is the set of 5-year experience bins. The parameter ϕ_s^x measures returns to one additional year of experience for workers in experience bin x. We thus allow experience returns to non-parametrically differ across life cycle stages (measured by experience bin x), allowing experience returns to change as workers grow older. $\gamma_{s,t}$ represents time effects on wage levels at time t, capturing aggregate productivity and price levels.

Equation (1) suffers from the well-known problem of collinearity between experience, individual effects, and time effects (Deaton, 1997): the sum $\sum_x D_{i,t}^x = 1$ 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, and wage growth over time can be induced by experience or by better aggregate economic conditions. To disentangle returns to experience from aggregate trends, we adopt the widely used HLT method (e.g., Huggett, Ventura and Yaron, 2011; Lagakos et al., 2018). This approach restricts experience returns to zero at a worker's old age, drawing on

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

the basic prediction of a large number of theories of life-cycle wage growth that there are negligible experience returns in the final working years (Rubinstein and Weiss, 2006). As a result, workers' wage growth in the final working years reflects only time effects. Implementing the HLT approach requires assumptions on two parameters: the number of years with no experience returns, and the depreciation rate. Following Lagakos et al. (2018), we consider 10 years at the end of the working life (31–40 years of experience) with no experience returns and a 0% depreciation rate, and these two parameters imply the restriction $\phi_s^{31-35} + \phi_s^{36-40} = 0$. Appendix C.1 provides further details on the approach.

2.2.2 Experience-wage profiles for workers at exporters and non-exporters

We use equation (1) to estimate experience-wage profiles. We focus on the effects of firms' export activity on wage profiles. We relegate a discussion of the role of the industry composition to Appendix D.1, where we show that industry characteristics do not drive the difference in experience returns between exporters and non-exporters. We always control for industry effects when comparing wage profiles between exporters and non-exporters.[7] 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.[8]

[7] Specifically, we estimate equation (1) separately for Brazilian workers at exporters and at non-exporters, for each 3-digit industry. We then apply identical weights (total industry-level employment) to construct aggregate profiles for workers at exporters and non-exporters, respectively.

[8] Appendix Figure D.3 shows that the relative differences in wage profiles between exporters and non-exporters are quantitatively similar if we assume no experience returns in the final 5 years. An alternative value of the 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.

2.3 Firm-level Wage Profiles and Export Destinations

2.3.1 Constructing experience-wage profiles at the firm level

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,

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

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 an exploration of changes in firms' export status. This equation involves a large number of firm-specific parameters and usually requires grouping firms into several groups for estimation (Bonhomme, Lamadon and Manresa, 2019). To exploit the firm-level information, instead of directly estimating equation (2), we make use of the HLT assumption 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 $(\gamma_{\omega,t} - \gamma_{\omega,t-1})$.[9] We can therefore construct an estimate for annual returns to experience in experience bin x with

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

where $\sum_{i \in \mathbb{I}(\omega)} D^x_{i,t} \Delta \log(w_{i,t}) / \sum_{i \in \mathbb{I}(\omega)} D^x_{i,t}$ is the average individual-level wage growth between $t-1$ and t, for a worker at firm ω ($i \in \mathbb{I}(\omega)$) in both periods and in experience bin $x \in \mathbb{X} = \{$1–5,...,36–40$\}$. In equation (3) we control for time-varying conditions (such as TFP growth, demand shocks) that alter wages for all workers within the firm. For example, if the firm raises every worker's wage by the same proportion under increased revenues after exporting, this common pay raise will not show up in the estimated experience returns of workers at firm ω. However, if the

[9] We use a single term to construct firm-specific wage trends if only one of the two terms $\sum_{i \in \mathbb{I}(\omega)} D^{31-35}_{i,t} \Delta \log(w_{i,t}) / \sum_{i \in \mathbb{I}(\omega)} D^{31-35}_{i,t}$ and $\sum_{i \in \mathbb{I}(\omega)} D^{36-40}_{i,t} \Delta \log(w_{i,t}) / \sum_{i \in \mathbb{I}(\omega)} D^{36-40}_{i,t}$ exists.

wage growth is relatively higher for young workers than old workers, the differential is interpreted as returns to experience.

2.3.2 Linking firm-level wage profiles to firm characteristics

In Table 1, 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 life-cycle wage growth of a worker staying at firm ω for 20 years from the beginning of the 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 experience minor returns to experience after 20 years of experience (Figure 1).[10]

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

This exporter premium in experience returns may reflect the exporters' advantages in workforce composition or unobserved technology (Islam et al., 2019). In Column (2) we therefore control for workers' education levels (average years of schooling and the share of workers with high-school degree), occupational composition (the shares of production workers and occupations intensive in cognitive tasks), and workers' average age. Because we do not have firm-level production data, we control for firm employment, which is associated with firm productivity (Hopenhayn, 1992), and we also control for firms' employment deciles to allow for nonlinear effects.[11] Finally, we control for firm fixed effects, capturing time-invariant unobserved factors.[12] After including these controls,

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

[11] The lack of production or value added information renders it impossible to directly estimate the firm's productivity and control for it, which could lead to an omitted-variable problem in our analysis and has to be left to future research.

[12] After controlling for firm fixed effects, 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 start exporting in the next year, and 13% of exporters stop

the resulting exporter 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.[13]

We explore the dependence of wage profiles on export destinations in Columns (3)–(6). In Column (3), for each exporter in each year, we include the ratio of the number of high-income destinations to the total number of export destinations. We also control for the number of export destinations, as the scope of destinations may matter. We find that firms that export more to high-income destinations exhibit steeper wage profiles. The coefficient suggests that other things held constant, a firm exporting solely to high-income countries exhibits a 13-percentage-point step-up in experience returns compared with a firm exporting solely to middle- and low-income countries.

In Columns (4)–(6), we exploit detailed firm-level data on export values available to use only in the 1997–2000 subperiod. Column (4) replicates the regression of Column (3) for the shorter 1997–2000 subperiod. We still find that exporting to high-income countries increases wage profiles, though the coefficients become noisier due to the 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 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 predict significantly higher returns to experience. We also find that controlling for export value per employee has little effect on the coefficients. In Column (6), we measure a firm's destination-specific exposure by using export-weighted GDP per capita across export destinations.[14] We find that exporting to destinations with higher income

exporting in the next year.

[13]Appendix Table D.1 reports how each control variable predicts experience returns and shows that experience returns are higher if there are more educated workers, more cognitively intensive occupations, and more nonproduction workers in the workforce, consistent with Islam et al. (2019). We also find that for the decline of the exporter premium in experience returns, only controlling for firm employment accounts for 57% of the overall decline after including all control variables, consistent with the tenet that more productive firms provide higher returns to experience and are more likely to select into exporting.

[14]To avoid that time trends of GDP per capita drive our results, we use each country's GDP per capita in 2000 to compute the firms' export-weighted GDP per capita across export destinations in 1997–2000. Appendix Table D.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.

significantly increases returns to experience.

In Appendix D.2, we provide a set of robustness checks. Among these exercises, we consider different classifications of high-income destinations and show that our empirical findings in Table 1 are robust.

2.4 Changes in Profiles Around Entry to High-income Destinations

2.4.1 Event study

In Appendix D.3, we perform an event study regarding firm entry into high-income destinations. We find that, after firms' first shipment to a high-income export market, returns to experience increase by 20 percentage points, a statistically significant effect at conventional confidence levels, whereas experience-wage profiles do not statistically significantly shift prior to firms' export entry. The increase in returns to experience stays roughly constant past first entry, indicating that exporting to high-income destinations is associated with persistently higher returns to experience. We find no statistically significant changes in returns to experience after entry into non-high-income destinations.

2.4.2 Propensity score matching estimator

Entry into export activity can be endogenous. To control for self-selection into exporting, in Appendix D.4 we apply a propensity-score matching estimator (Heckman, Ichimura and Todd, 1997). The idea of the matching estimator is to choose an appropriate group of non-exporters as control group, based on predicted export probabilities. We first estimate each firm's probability to start to export, while controlling for a broad range of pre-exporting firm characteristics, and then choose the control group based on nearest-neighbor matching. The identifying assumption is that controlling for an exhaustive set of firm-level characteristics turns observed export-market entry into a random event unrelated to any systematic firm attribute. The estimation results suggest that exporting to high-income destinations raises 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 previous findings. For entry to non-high-income destinations, we find no statistically significant changes in returns to experience after export entry.

2.4.3 Brazilian currency crisis

Recent studies exploit substantive 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 D.5, we use the Brazilian currency crisis in 1999 when the Brazilian Real experienced a 60% devaluation against the U.S. dollar 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 D.6, we construct a panel of young workers that first appear in RAIS within 5 years after completing school.[15] Using this sample, we still find that previous experience at exporters (especially at 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 a similar magnitude to our previous findings. We also show similar results for workers displaced when large firms suddenly close down.

The similarity between worker-level and firm-level results, and across different estimation methods, contributes to our confidence that steeper experience-wage profiles at exporters (than at non-exporters) reflect the effect of a firm's entry into more advanced export destinations.

[15] This restricted sample has several advantages. 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, breaks in employment history for reasons such as unemployment (which does not necessarily contribute to more experience) do not result in a collinearity problem between experience and year effects. We therefore no longer need the HLT approach in estimation.

3 Model

To isolate factors behind the impact of export activity on wage profiles and to assess the aggregate implications, we develop a quantitative model. Motivated by our evidence and the quantitative literature on earnings dynamics, we posit that wage profiles reflect human capital formation as well as changes in worker-firm rent sharing. We focus on a steady state in which aggregate variables are constant. We index workers by i and firms by ω or ν.

3.1 Model Setup

3.1.1 Workers

Age structure. Overlapping generations of workers participate in the labor market at age $a = 1, 2, .., A$. Workers of age A retire at the end of each period and are replaced with a cohort of entering workers of age 1. Each cohort's size is normalized to 1 so that the total population is A. The introduction of a workers' age structure equips the model with the dynamics to generate wage profiles comparable to our empirically constructed wage profiles. Moreover, returns to human capital accumulation decline with age and most senior workers enjoy good bargaining positions, so our model generates numerically minor experience effects in the final working years, which is a key assumption of the HLT approach.

Utility. Workers enjoy linear utility from consumption of a nontraded 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. At the beginning of each period, existing jobs are terminated at an exogenous rate κ. New entrants of age 1 begin their careers as unemployed individuals. Unemployed and employed persons randomly meet job vacancies at the respective rates λ_U and λ_E. Let U be the measure of unemployed persons prior to job search, and $\eta \in [0, 1)$ the search effort of employed persons relative to the unemployed, whose search effort is normalized to 1. The meeting rates λ_U and λ_E are endogenously determined: $\lambda_U = \chi(V/[U + \eta(A - U)])$ and $\lambda_E = \eta\lambda_U$, where $V/[U + \eta(A - U)]$ is the ratio of firms' vacancies to total search efforts. The function $\chi(\cdot)$ governs the matching process.

When an unemployed worker meets a job vacancy, she accepts the job with certainty under the assumption that unemployment is equivalent to employment at the least productive firm. Similar to Bagger et al. (2014), this assumption avoids the complication of heterogeneous reservation wages for workers of different human capital levels and ages. 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 subsection 3.2.1 below.

Wage. At firm ω, wages differ between workers. A worker i of age a receives a wage

$$w_i^a(\omega) = r_i(\omega)\tilde{z}(\omega)\left[h_i^a - s^a(h_i^a, \omega)\right], \tag{4}$$

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 optimal time (in terms of units of labor) spent on human capital accumulation, to be derived in subsection 3.2.3 below. As in Bagger et al. (2014), the worker and the firm negotiate the contractual piece rate $r_i(\omega)$, where $r_i(\omega) \in [0, 1]$ can be viewed as the portion of revenues generated by worker i at firm ω and accruing to the worker. The portion is worker-firm-specific and depends on the history of wage bargaining between worker i and firm ω over the job surplus, as described below.

Human capital accumulation. For tractability, we restrict our attention to a single dimension of general human capital.[16] New entrants of age 1 are endowed with human capital normalized to

[16]Firm-specific components of human capital have been found to be less relevant for wage growth than general human capital (Altonji and Shakotko, 1987; Lazear, 2009; Kambourov and Manovskii, 2009). Our worker-level evidence suggests that most of the human capital gained at exporters is portable when workers switch firms. A focus on general human capital is common in the quantitative literature on earnings dynamics (e.g., Bagger et al., 2014;

$h_i^1 = 1$. Employed workers may accumulate human capital on the job. We assume that a worker's human capital evolves from age a to age $a+1$ with

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

where δ_h is the depreciation rate, $\phi^E(\omega)$ captures the increment in human capital per unit of time spent on building skills, and the power $\alpha \in (0,1)$ regulates the diminishing marginal benefits of time $s^a(h_i^a,\omega)$ for human capital accumulation. A key feature of our model is the dependence of the increment in human capital on the firm's choice of export destinations:

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

We model the human capital increment as a Cobb-Douglas function of knowledge inside and outside the firm, similar to Monge-Naranjo (2019), where γ_1 and γ_2 represent the respective elasticities of the increment to internal and external knowledge. We use firm productivity $z(\omega)$ to proxy internal knowledge—the stock of productive ideas within the firm. $\phi^O(\omega)$ summarizes the outside set of productive ideas in the firm's markets and is available to workers at 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 accessible when selling to market n. Then $\phi^O(\omega) = \sum_n k_n(\omega)\Lambda_n$ is a weighted average of knowledge across destinations. We further discuss this learning function and its relationship to the literature in Appendix E.1.

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 $z(\omega)$ from a 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 its variety requires $1/z(\omega)$ efficiency units of labor.

Manuelli and Seshadri, 2014).

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

Trade. There are countably many countries $n = 1, 2, ..., N$. The home country is the first market $n = 1$, and all other markets are foreign destinations. The home country is a small open economy so that aggregate variables in foreign countries are invariant to conditions at home. Under monopolistic competition, the demand for a firm ω's variety 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. The price of a variety in market n is $p_n(\omega) = y_n(\omega)^{-\frac{1}{\sigma}} P_n Y_n^{\frac{1}{\sigma}}$, and the revenue in market n is $p_n(\omega) y_n(\omega) = y_n(\omega)^{\frac{\sigma-1}{\sigma}} P_n Y_n^{\frac{1}{\sigma}}$. When selling to market n, firms in the home country incur an iceberg transport cost τ_n as well as a fixed cost f_n in terms of final goods in the home market. We assume no trade costs of selling to the home market ($\tau_1 = 1$ and $f_1 = 0$).

Hiring costs. Firms post vacancies to meet workers. Posting v vacancies costs $c_v v^{1+\gamma_v}/(1+\gamma_v)$ units of final goods. In the quantitative analysis, we assume $\gamma_v > 0$. This assumption generates an exporter premium because it is increasingly costly to hire additional workers so that a firm needs to generate additional revenues per worker to expand. Let $v(\omega)$ be the optimal number of vacancies for firm ω, as detailed below. The total number of vacancies is $V = \int v(\omega)\, \mathrm{d}\Phi(z(\omega))$. We define $F(z(\omega)) = \int_{z_{\text{min}}}^{z(\omega)} v(\nu)\, \mathrm{d}\Phi(z(\nu))/V$ as the offer distribution.

Firm revenue. Aggregating over destinations, we can compute the firm's total revenue (gross of fixed export costs) as $\sum_n y_n(\omega)^{\frac{\sigma-1}{\sigma}} P_n Y_n^{\frac{1}{\sigma}}$, where $y_n(\omega)$ is the value of exports to market n (zero if no sales at n). In its optimal export entry and export volume decisions, the firm takes into account: (1) total output given by $z(\omega)h(\omega)$, where employment $h(\omega) = \sum_a \int_{i \in \mathbb{I}(\omega)} (h_i^a - s^a(h_i^a, \omega))\mathrm{d}i$ is the measure of efficiency units employed at firm ω across workers of different ages; (2) the iceberg and fixed export costs τ_n and f_n; and (3) the impact of export destinations on workers' human capital, which affects the future job surplus. We will specify the firm's choice of export destinations in subsection 3.3 below. With a slight abuse of notation, we define the revenue per unit of labor

$\tilde{z}(w) \equiv \sum_n y_n(\omega)^{\frac{\sigma-1}{\sigma}} P_n Y_n^{\frac{1}{\sigma}} / h(\omega)$, which plays the role of labor productivity in our model.

3.2 Solving for a Worker's Wage and Human Capital Investment

3.2.1 Wage bargaining and job-to-job moves

As described in equation (4), a worker's wage is $w_i^a(\omega) = r_i(\omega)\tilde{z}(\omega)\left[h_i^a - s^a(h_i^a, \omega)\right]$, where the piece rate $r_i(\omega)$ is the share of revenues accruing to the worker. The piece rate is worker-firm specific and depends on the worker-firm bargaining history. We now describe the process that determines $r_i(\omega)$, following CPR. The vector $\mathbf{x}(\omega) = \left(z(\omega), \{y_n(\omega)\}_n, \{h_i^a\}_{i \in \mathbb{I}(\omega)}\right)$ collects the firm-level state variables, including productivity, export status, and characteristics of the firm's workforce $\mathbb{I}(\omega)$. These state variables are given when the worker and firm bargain and determine the revenue per labor $\tilde{z}(\omega)$ and human capital increment $\phi^E(\omega)$.[17] We denote with $V^a(r, h_i^a, \mathbf{x}(\omega))$ the value of a job for worker i of age a with piece rate r. We denote the joint (worker + firm) value of the job with $M^a(h_i^a, \mathbf{x}(\omega))$, which does not depend on r because the worker's piece rate only determines the distribution of surplus between worker and firm but not the total.

Unemployed persons. When an unemployed person i meets and accepts a job at firm ω, the person engages in Nash bargaining with the employer over the job surplus $M^a(h_i^a, \mathbf{x}(\omega))$. The outside option of the worker is the unemployment value $V_U^a(h_i^a)$, whereas the outside option for the firm is set to 0. We assume that the worker's bargaining power is $\beta \in (0, 1)$. The piece rate r maximizes

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

[17] In our model, export decisions are separate from the bargaining process. In practice, firm divisions responsible for product and sales decisions may plausibly be distinct from those responsible for human resources and thus the worker contracting and bargaining process. The assumption helps with computational tractability. Our bargaining and contracting setup involves the worker-related wage and work time choices but differs from the comprehensive contracts in the Menzio and Shi (2011) model, where the worker and the firm also contract over payoff-relevant decisions on the firm side.

Optimality implies a piece rate r that satisfies the first-order condition $V^a(r, h_i^a, \mathbf{x}(\omega)) = V_U^a(h_i^a) + \beta\left[M^a(h_i^a, \mathbf{x}(\omega)) - V_U^a(h_i^a)\right]$. The worker receives the outside value of unemployment plus a portion β of the extra value of holding a job relative to unemployment $M^a(h_i^a, \mathbf{x}(\omega)) - V_U^a(h_i^a)$. We discuss the explicit expressions for $V^a(r, h_i^a, \mathbf{x}(\omega))$, $V_U^a(h_i^a)$ and $M^a(h_i^a, \mathbf{x}(\omega))$ below.

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 ν. When there is an outside offer, there are three scenarios with different implications for a revision of the employed person's piece rate.

1. The poaching firm cannot offer the worker a value higher than the worker's current value, so that $V^a(r, h_i^a, \mathbf{x}(\omega)) > M^a(h_i^a, \mathbf{x}(\nu))$. In this case, the outside offer does not affect the worker's wage and the piece rate r does not change.

2. The job at the poaching firm ν is more valuable than the worker's current job at firm ω, so that $M^a(h_i^a, \mathbf{x}(\nu)) > M^a(h_i^a, \mathbf{x}(\omega))$. In this case, the worker moves to the poaching firm. For wage bargaining at the poaching firm, the worker's outside option is the job value at the current firm $M^a(h_i^a, \mathbf{x}(\omega))$. Nash bargaining determines the piece rate r' at the poaching firm:

$$\max_{r'} \left[V^a(r', h_i^a, \mathbf{x}(\nu)) - M^a(h_i^a, \mathbf{x}(\omega))\right]^{\beta} \left[M^a(h_i^a, \mathbf{x}(\nu)) - V^a(r', h_i^a, \mathbf{x}(\nu))\right]^{1-\beta}. \tag{8}$$

   Optimality implies that the piece rate r' at the poaching firm satisfies the first-order condition $V^a(r', h_i^a, \mathbf{x}(\nu)) = M^a(h_i^a, \mathbf{x}(\omega)) + \beta\left[M^a(h_i^a, \mathbf{x}(\nu)) - M^a(h_i^a, \mathbf{x}(\omega))\right]$.

3. The job at the current firm ω is more valuable than the job at the poaching firm ν, but the value of employment is so low that the poaching firm's offer is attractive to the worker because $V^a(r, h_i^a, \mathbf{x}(\omega)) < M^a(h_i^a, \mathbf{x}(\nu)) < M^a(h_i^a, \mathbf{x}(\omega))$. To prevent the worker from separating, the current firm renegotiates with the worker over a new division of the job surplus. The worker now uses the poaching firm's job value $M^a(h_i^a, \mathbf{x}(\nu))$ as the outside option. The worker stays at the current firm and receives the new piece rate r' under Nash bargaining similar to equation (7),

where instead of the value of unemployment the worker uses the poaching firm's job value as outside option. Optimality implies that the new piece rate r' satisfies $V^a(r', h_i^a, \mathbf{x}(\omega)) = M^a(h_i^a, \mathbf{x}(\nu)) + \beta \left[M^a(h_i^a, \mathbf{x}(\omega)) - M^a(h_i^a, \mathbf{x}(\nu))\right]$.

3.2.2 Value of employment

We present the formula for the value of employment in Appendix E.2. $V^a(r, h_i^a, \mathbf{x}(\omega))$ is a function of the current wage $r\tilde{z}(\omega)(h_i^a - s^a(h_i^a, \omega))$ and its future value, which depends on human capital in the next period given by equation (5) and on whether the worker stays or leaves the firm. The unemployment value is $V_U^a(h_i^a) = \min_\omega M^a(h_i^a, \mathbf{x}(\omega))$. At the conclusion of the bargaining process (subsection 3.2.1 above), the firm and the worker contract on a specific piece rate r that delivers the value of employment.[18]

3.2.3 Job value and human capital investment

Job value. To solve for human capital investment, we need to specify the joint (firm + worker) value of a job. In Appendix E.2 equation (E.2), we show that the job value includes current firm revenues $\tilde{z}(\omega)(h_i^a - s^a(h_i^a, \omega))$ and the future job value. The difference between the job value and the value of employment is the firm's value of the job, which mainly captures the portion of current and future revenues generated by the worker and accruing to the firm.

Human capital investment. We assume that the worker and the firm jointly choose the time spent on human capital accumulation $s^a(h_i^a, \omega)$ to maximize the job surplus $M^a(h_i^a, \mathbf{x}(\omega))$ similar to Acemoglu and Pischke (1999), while the worker and the firm simultaneously bargain over the split of the maximal surplus. Using the evolution of human capital (5) in the joint job value (E.2),

[18] CPR analytically solve for the piece rate and show that it increases with the worker's current outside option and depends on the history of the worker's outside offers from poaching firms. Our model with endogenous human capital formation does not yield an analytical solution for the piece rate. We therefore rely on numerical analysis to first solve for the value of employment at any piece rate r and then find the specific piece rate that delivers the value determined by the worker's bargaining outcome.

the first-order condition for the optimal time spent on human capital accumulation implies

$$s^a(h_i^a, \omega) = \left(\frac{\alpha \phi^E(\omega)}{\tilde{z}(\omega)} \frac{\partial M^a(h_i^a, \mathbf{x}(\omega))}{\partial h_i^{a+1}} \right)^{\frac{1}{1-\alpha}} . \tag{9}$$

The optimal time spent on human capital accumulation increases with marginal benefits, which are determined by the human capital increment per time $\phi^E(\omega)$ and the marginal return of human capital $\partial M^a(h^a, \mathbf{x}(\omega))/\partial h^{a+1}$. Exporting to destinations with high knowledge stocks leads to a higher value of $\phi^E(\omega)$ and thus encourages human capital investment. As workers grow older, the gains of human capital accumulation tend to decline. In particular, for a worker who retires at the end of a period (so the next-period value is 0), $\partial M^a(h^a, \mathbf{x}(\omega))/\partial h^{a+1} = 0$. As a consequence, there is no human capital investment one period before retirement, and our model can numerically generate vanishing experience effects in the final working years.

3.3 Solving for a Firm's Export Entry by Destination and Vacancy Posting

To account for the impact of firms' export destinations on workers' human capital accumulation, we posit 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:

$$\begin{aligned} \max_{\{y_n(\omega)\}} & \sum_a \int_{i \in \mathbb{I}(\omega)} M^a(h_i^a, \mathbf{x}(\omega))\, \mathrm{d}i - \sum_n \mathbf{1}_{\{y_n(\omega)>0\}} P_1 f_n \\ & = \underbrace{\sum_n \mathbf{1}_{\{y_n(\omega)>0\}} \left(y_n(\omega)^{\frac{\sigma-1}{\sigma}} P_n Y_n^{\frac{1}{\sigma}} - P_1 f_n \right)}_{\text{revenues net of fixed export costs}} + \underbrace{\sum_a \int_{i \in \mathbb{I}(\omega)} M^{a,\textit{future}}(h_i^a, \mathbf{x}(\omega))\, \mathrm{d}i}_{\text{future job value}} \\ & s.t. \underbrace{\sum_n \tau_n y_n(\omega) = z(\omega) h(\omega),}_{\text{output capacity}} \quad \underbrace{\mathbf{x}'(\omega) = \Gamma(\mathbf{x}(\omega))}_{\text{law of motion for firm's state}} , \end{aligned} \tag{10}$$

where $\mathbf{1}_{\{y_n(\omega)>0\}} \in \{0, 1\}$ indexes the decision of exporting to market n. The second line is obtained by decomposing the job value $M^a(h_i^a, \mathbf{x}(\omega))$ into the current revenue and the future value

$M^{a,\textit{future}}(h_i^a, \mathbf{x}(\omega))$.[19] 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 ($\mathbf{1}_{\{y_n(\omega)>0\}} \in \{0, 1\}$ for each market $n = 1, ..., N$). To solve the choice of export destinations, we first evaluate the benefit in equation (10) given each feasible combination of export destinations and then choose the optimal combination of export markets that delivers the highest benefit.

In Appendix E.3, we show that the optimal amount of vacancies is determined such that the marginal costs of posting a vacancy equal the aggregate value per vacancy from hiring unemployed workers and poaching employed workers.

3.4 General Equilibrium

The analysis so far studies 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.[20] We abstract from savings, so all firm profits (revenues net of fixed export costs) are spent on final goods. Balanced trade requires that, when the goods market clears, the firms' total export value equals the total value of imported varieties in the home country. In Appendix E.4, we provide a detailed equilibrium definition.

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

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

3.5 Export Activity and Wage Profiles

Using wage equation (4), a worker i's within-job wage growth at firm ω is

$$\Delta \log w_i^a(\omega) = \underbrace{\Delta \log h_i^a}_{\text{change in human capital}} + \underbrace{\Delta \log \left(1 - \frac{s^a(h_i^a, \omega)}{h_i^a}\right)}_{\text{change in work time}} + \underbrace{\Delta \log \tilde{z}(\omega)}_{\text{change in labor productivity}} + \underbrace{\Delta \log r_i(\omega)}_{\text{change in piece rate}} . \tag{11}$$

Export activity changes wage profiles within the firm through four channels. First, export activity affects workers' human capital increment, by shifting the mixture of destinations to which workers are exposed under equation (6). If workers' human capital growth depends on the external environment ($\gamma_2 > 0$), and knowledge stocks Λ_n vary across destination markets, then export activity alters wage profiles through the human capital channel. Second, due to changes in human capital investment, workers' work time also changes. Young workers spend more time on human capital accumulation than old workers, so work time increases over the life cycle, and thus changes in work time move wage profiles. Third, firms' labor productivity $\tilde{z}(\omega)$ moves wages directly (in a generalized model export activity could affect inherent productivity directly). The labor productivity change is identical for young and old workers within a firm and thus does not directly affect wage profiles. However, increased labor productivity offers larger room for the current workers' wages to grow through wage renegotiations when workers, especially young, are poached by outside firms. The fourth term reflects resulting changes in the piece rate from renegotiation.

The impact of export activity on wage profiles matters for the aggregate economy. In Appendix E.5 we show that, under certain assumptions, the gains from trade in our model can be decomposed into changes in real income per efficiency labor, which resembles the well-studied formula (e.g., Arkolakis, Costinot and Rodríguez-Clare, 2012; Costinot and Rodríguez-Clare, 2014), and changes in the average level of employees' efficiency labor. Changes in the human capital of workers reflect both the impact of export destinations on wage profiles and workers' reallocation toward exporters where workers may enjoy faster human capital accumulation.

In our computational implementation of the model, we consider steady state and do not incorporate dynamics in export status or revenues.[21]

4 Quantification

In this section, we calibrate our model to the Brazilian data. Through the lens of our quantitative model, we then explore the determinants of 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 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, 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 compute a firm's export decision, we need to compare $2^N - 1$ feasible combinations of N destination markets—a computationally demanding procedure for large N. We therefore aggregate all destination markets (other than Brazil) into 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.[22]

[21] We found the model to be computationally intractable when firms and workers are both forward-looking and form expectations of firms' future productivity shocks for their decisions. When we quantitatively compute gains in experience returns immediately following export entry, we use a partial-equilibrium analysis similar to recent research (e.g., Buera, Kaboski and Townsend, 2021; Buera, Kaboski and Yongseok, 2021), implementing alternative realizations of export costs for each firm in steady state.

[22] Africa and South America do not have high-income countries. Because non-high-income countries in Oceania account for a negligible share (less than 0.01%) of the Brazilian manufacturing exports in 2000, we omit them from the analysis.

4.2 Calibration

To proceed, we specify the function $\chi(\cdot)$ that determines the meeting rate between unemployed persons and firms. It is common to use a Cobb-Douglas job matching function between searchers and vacancies (e.g., Shimer, 2005), which implies $\chi(x) = c_M x^{\phi}$, where $0 < \phi < 1$ is the elasticity of job matches to vacancies. To capture the idea that some small firms also export, we assume that time-invariant export fixed costs $\{f_n\}_{n=2,...,N}$ follow a log-normal distribution, $\log f_n \sim \mathcal{N}(\log \bar{f}_n, \sigma_f^2)$, 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 would make the model intractable.[23] 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.[24]

The calibration must determine the following parameters: the worker's lifetime A, the discount rate ρ, the number of destinations N, the parameters governing labor search and wage bargaining $\{\phi, c_M, \kappa, \eta, \beta\}$, human capital depreciation and returns $\{\delta_h, \alpha, \mu, \gamma_1, \gamma_2, \Lambda_n\}$, the shape parameter ζ of the productivity distribution, the elasticity of substitution between varieties σ, the demand and fixed costs of foreign markets $\{P_n^{\sigma} Y_n \tau_n^{1-\sigma}, \bar{f}_n, \sigma_f\}_{n=2,...,N}$, the constant and curvature of vacancy costs $\{c_v, \gamma_v\}$, and import demand $\bar{M}^I (p^I)^{1-\sigma}$.

4.2.1 Parameter choices prior to solving the model

Panel A of Table 2 lists the parameters that we set without solving the model. We calibrate a model of annual frequency and pick an annual discount rate ρ of 0.04. Every person works for 40 years, so we set the total work time to $A = 40$ years.

We set the elasticity of job matches to vacancies to $\phi = 0.3$ following Shimer (2005)'s estimate

[23] Under stochastic export-market conditions, the worker needs to form expectations about firms' future export status and the firm needs to take into account the workers' different turnover rates under a varying export status.

[24] 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 of analytically solving the exact requirement for the finite aggregation of sales in our model, we require $\zeta > \sigma - 1$ in the calibration.

for the U.S. economy. This parameter is commonly applied to other countries in the development literature (e.g., Feng, Lagakos and Rauch, 2018). We follow Manuelli and Seshadri (2014) and 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 countries into our $N = 10$ groups using Brazil's export values as weights. We normalize Brazil's knowledge stock to 1.

We set the elasticity of substitution between varieties to $\sigma = 5$, a common value in the trade literature (Head and Mayer, 2014). For the convexity in vacancy costs we use $\gamma_v = 1.5$ using Dix-Carneiro et al. (2021)'s estimate for Brazilian firms.

4.2.2 Parameters calibrated by solving the model

We jointly estimate the remaining 29 parameters (listed in Panel B of Table 2) to match 29 data moments on trade, the labor market, and wage profiles. We report the moments used in our calibration in Appendix Table F.1.

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—and use the average from reduced-form results based on the matching estimator in Appendix Table D.11. 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 equation (11) shows, export entry leads to changes in the increment of human capital per time spent, changes in work time, and higher labor revenues that affect wage profiles by widening the scope of wage renegotiations. We discuss the details on computation in Appendix F.1.

To inform our choice of moments for the determination of parameters, we trace the dependence of certain parameters to specific moments. For example, export demand at 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. We infer the bargaining power β mainly from the increase of workers' wages with firm size. A larger β implies that workers obtain proportionally higher shares of the surplus at larger and more productive firms. The on-the-job search intensity η relates to the share of new hires that were employed in other firms (last year).

Finally, for a given strength of wage renegotiations (mainly governed by the workers' bargaining power β and the on-the-job search intensity η), average experience returns are informative of the magnitude of the human capital increment shifter μ. The increase of experience returns with firm size and the change in experience returns due to export entry into high-income countries regulate the dependence of the human capital increment on firm productivity γ_1 and on the destination-specific knowledge stock γ_2, respectively.[25]

4.3 Calibration Results

Table 2 presents the internally calibrated parameters. Our parameter values are similar to those in the literature. For example, our calibrated job destruction rate and on-the-job search intensity are 0.16 and 0.12, respectively, and close to 0.15 and 0.11–0.16 found in Fajgelbaum (2020) for Argentine manufacturing firms. Our calibrated wage bargaining power $\beta = 0.6$ is comparable to estimates for bargaining models with wage renegotiation and human capital accumulation: Gregory (2021) estimates the bargaining power β to be 0.66 at German employers, whereas Bagger et al. (2014) find β to be between 0.29–0.32 at Danish firms. Appendix Table F.1 shows that our model closely matches the targeted moments. In Appendix F.2 we discuss untargeted moments in the calibrated model and their similarity to data moments, providing additional support for the applicability of the model. In particular, our model-generated differences in experience effects between exporters and non-exporters are similar to those in the data, and our model predicts negative changes in experience effects due to export entry into non-high-income countries in line with the

[25]There are no direct correspondences between $\{\gamma_1, \gamma_2\}$ and the data, so our estimation relies on indirect inference (Gouriéroux and Monfort, 1996), by which the researcher picks the structural parameters that minimize the distance between the estimates from an econometric model on the real data and the estimates from the same econometric model estimated on the simulated data. Appendix Table G.1 reports the Jacobian matrix showing how changes in γ_1 and γ_2 affect the moments and confirms that the slope of experience returns with respect to firm size 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.

reduced-form evidence in Appendix Table D.13.

4.4 Decomposing the Returns to Experience

With the calibrated model, we now turn to understanding the factors that shape experience-wage profiles. In Appendix F.3, we show that human capital accumulation accounts for about 70% of workers' overall wage growth over the life cycle. There are diminishing returns to human capital investment, however, so human capital growth can only account for 55% of the difference in lifetime wage growth between exporters and non-exporters. We also find that human capital accounts for half of the gains in experience returns after export entry into high-income countries.

5 Quantitative Evaluation

We now use 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 provide robustness checks regarding model assumptions and parameters.

5.1 Gains from Trade

Table 3 reports the gains from trade, computed in the calibrated model as the ratio of real consumption with trade to real consumption in autarky. For autarky, we set Brazil's bilateral trade costs with foreign economies to infinity. The overall gains from trade are 7.78%. 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. We allow for unemployment and show that trade openness increases firms' overall vacancy postings, which also leads to a 0.51% employment gain. With trade openness, workers and firms choose to set aside more time for human capital accumulation, so the average work time decreases by 0.46% after trade openness.

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.

5.2.1 Decomposition of human capital growth

Appendix Figure G.1 compares the distribution of workers' human capital growth between autarky and trade openness in the calibrated economy, indicating faster human capital growth after trade integration. Motivated by common decompositions of productivity growth (see, e.g., Foster, Haltiwanger and Krizan, 2001), we decompose changes in human capital growth under trade openness to reflect the contributions of different forces. We denote the average per-period human capital growth in the economy with $g_h = \int \ell(\omega) g_h(\omega)\, \mathrm{d}\Phi(z(\omega))$, where $\ell(\omega)$ is firm ω's employment share, and $g_h(\omega)$ is average growth in human capital per period at firm ω. The changes in the growth of human capital can thus be written as

$$g_h' - g_h = \int \underbrace{[\ell'(\omega) - \ell(\omega)][g_h(\omega) - g_h]}_{\text{between-firm term}} + \underbrace{\ell(\omega)[g_h'(\omega) - g_h(\omega)]}_{\text{within-firm term}} + \underbrace{[\ell'(\omega) - \ell(\omega)][g_h'(\omega) - g_h(\omega)]}_{\text{cross-firm term}} \,\mathrm{d}\Phi(z(\omega)). \tag{12}$$

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

Table 4 reports the decomposition results. The between-firm term contributes only slightly to the increase in human capital growth, reflecting the trade-induced labor reallocation toward more productive firms in a Melitz (2003) model. The within-firm term contributes the most to the overall increase in human capital growth from autarky to the calibrated economy. Panel (b) of Table 4 further decomposes the within-firm term according to a firm's export status in the calibrated economy. Consistent with relatively higher knowledge stocks at high-income destinations compared with Brazil, firms that solely export to high-income destinations contribute the most to the increase in human capital growth between autarky and the calibrated economy, followed by the importance of 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.[26] This result confirms that high-income destinations are associated with increased human capital formation.

5.2.2 Model with identical returns to firm learning

We now compare our baseline model to a model with neither firm-specific nor trade-specific human capital accumulation. Under the functional form of the human capital increment per time $\phi^E(\omega) = \mu z(\omega)^{\gamma_1} \left(\phi^O(\omega)\right)^{\gamma_2}$ in equation (6), γ_1 is the elasticity of the human capital increment to firm productivity and governs how the labor allocation between firms affects human capital accumulation. The parameter γ_2 is the elasticity of the human capital increment to destination-specific knowledge $\phi^O(\omega)$, shaping how entry into export destinations affects human capital formation. We now set $\gamma_1 = \gamma_2 = 0$ such that all firms have the same human capital increment, and learning-by-exporting is no different from general learning, and recalibrate this alternative model to the targeted data moments in Appendix Table F.1.

Table 5 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-market participation) raise opportunity costs of human capital investment and lead to lower investment levels. In contrast, in the baseline model with $\gamma_1 > 0$ and $\gamma_2 > 0$, the human capital increment increases with firm productivity and destination-specific knowledge, offsetting the effects of opportunity costs. The contrasting results highlight the importance of modeling the dependence of the human capital increment on firm productivity and destination-

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

specific knowledge to successfully match changes in experience returns across firms and after export entry. The gains in human capital from trade are negligible in the alternative model since trade does not directly affect the human capital increment.[27]

5.2.3 Trade liberalization with different destinations

Given the potentially large differences in knowledge stocks across destinations, we explore how the effects of trade liberalization vary by destination. In the upper two rows of Table 6, we compute changes in real income and human capital after a 10% decline in Brazil's variable trade costs to high-income and non-high-income destinations, respectively. Lowering trade costs to high-income destinations by 10% increases 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% reduces 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 induces productive firms to allocate labor away from high-income export destinations. In addition, higher revenues per efficiency labor due to exporting increase the opportunity costs of investing in human capital. It is worth noting that our focus lies on steady-state comparisons (abstracting from computationally intractable transitional dynamics). At impact, it is possible that lower variable trade costs to non-high-income destinations leads to short-run gains due to changes in wages and prices.

In the lower three rows of Table 6 we report changes in real income and human capital after a 10% decline in Brazil's variable trade costs to main export destinations.[28] In line with our previous results on high-income countries, lowering trade costs to Europe and the United States leads to large gains in real income, which are mainly driven by gains in workers' human capital. On the

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

[28] Our baseline model is calibrated to the export data in 2000, when non-high-income countries in Asia (mainly China) were still a relatively small export destination for Brazil. Brazil's exports to China grew fast over the recent decades (Appendix A.1). 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.

other hand, the wage and price gains from lowering trade costs to China or South America are largely offset by drops in human capital levels.

5.3 Robustness Checks

In Appendix F.4, we provide several robustness checks regarding the key parameters. We also consider an alternative way of modeling human capital accumulation through learning-by-doing. We find that across all these alternative specifications, human capital generally contributes to the gains in trade, with an increase in real consumption ranging from 2.13% to 5.72%.

6 Conclusion

Using Brazilian administrative employer-employee and customs data, we document that workers' within-job life-cycle 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 dynamic firm-level model with export market entry, worker-firm wage bargaining, and workers' human capital accumulation. In the model, workers' within-job pay grows due to human capital growth, changes in the time allocated to working or learning, and wage renegotiations in response to poaching attempts. We consider the possibility that the human capital increment can 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.

Trade affects workers' wages in multiple ways. Understanding the different mechanisms by which wages can move with trade is of crucial importance to assess aggregate welfare and inequality. This study takes a first step to empirically and quantitatively understand the effects of trade on workers' life-cycle 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 can ultimately lead to a better understanding of the welfare impact of globalization.

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Table 1: 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

Notes: Estimates from regressions of firm-year-level returns to 20 years of experience on firm characteristics. Reference group: non-exporters. Controls: 1) average years of schooling; 2) share of workers with high-school degree; 3) share of occupations intensive in cognitive tasks; 4) share of production workers; 5) average worker age; (6) firm employment; and (7) firm employment percentiles (divided into 10 bins) within each industry-year bin. Countries are classified as high-income according to the World Bank in 2000, which sets the high-income threshold at a GNI per capita of US$9,265 in 2000. See Appendix D.2 for several robustness checks to the high-income classification. Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%. *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

Table 2: Parameters Values

Parameter	**Notation**	**Value**	**Source**
Panel A: Parameter Choices Prior to Solving the Model			
Total work 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. (2021)
Panel B: Parameters Calibrated by Solving the Model			
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)	
Standard deviation of export costs	σ_f	1.48	
Import demand	$\bar{M}^I (p^I)^{1-\sigma}$	0.14	

Notes: The stock of knowledge is the average across $N = 10$ destination markets, with the standard deviation in parentheses. The values for export demand $P_n^\sigma Y_n \tau_n^{1-\sigma}$ and export fixed costs $\bar{f}_n$ are averages across $N = 9$ foreign markets, with the standard deviation in parentheses. Demand depends on a standardization; we normalize the domestic price index to $P_1 = 1$ in the calibrated equilibrium.

Table 3: 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%

Notes: Gains from trade computed in the calibrated model as the ratio of real consumption with trade to real consumption in autarky. For autarky, Brazil's bilateral trade costs with foreign economies are set to infinity.

Table 4: 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%

Notes: Panel (a) reports decomposition of human capital growth according to equation (12). Panel (b) further decomposes within-firm term according to a firm's export status in calibrated economy.

Table 5: Comparing Baseline Model to Model with Common Learning Returns

	Increase of Experience Returns with Firm Size	ΔExperience Returns from Exports to High-income Dests	Gains from Trade	
			Real Income	Human Capital
(1) Data	0.15	0.22		
(2) Baseline	0.15	0.21	7.78%	3.98%
(3) Common learning returns ($\gamma_1 = \gamma_2 = 0$)	-0.20	-0.03	5.05%	0.17%

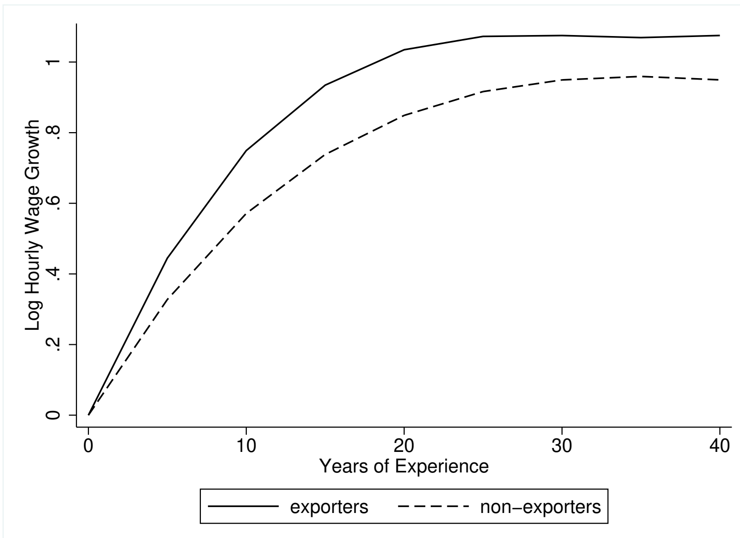
Notes: Comparison of (1) data moments to moments in both (2) calibrated baseline model and (3) alternative model with no firm- or export-specific learning returns ($\gamma_1 = \gamma_2 = 0$). For re-calibration of alternative model, we do not target the increase of experience returns with firm size and the change in experience returns due to export entry into high-income countries, which mainly discipline the parameters γ_1 and γ_2 (but results are similar if these two moments are being targeted). The alternative model matches all other targeted moments in Table F.1 well.
Data Sources: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

Table 6: Gains from 10% Decline in Variable Export Costs

Export destinations	$\frac{\text{Export}}{\text{Output}}$	GDPPC (Brazil=1)	10% Decline in Trade Costs	
			$\Delta\%$Real Income	$\Delta\%$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 area & United States	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%

Notes: Proportional changes in real income and human capital after a 10% decline in Brazil's variable export costs to different export destinations. For the calibration China, we use Brazil's export-to-output ratio and the relative GDP per capita between China and Brazil in 2019.

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



Notes: Experience-wage profiles for workers at exporters and non-exporters, from estimating equation (1) on the Brazilian data between 1994–2010. We assume no experience returns in final 10 years. *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

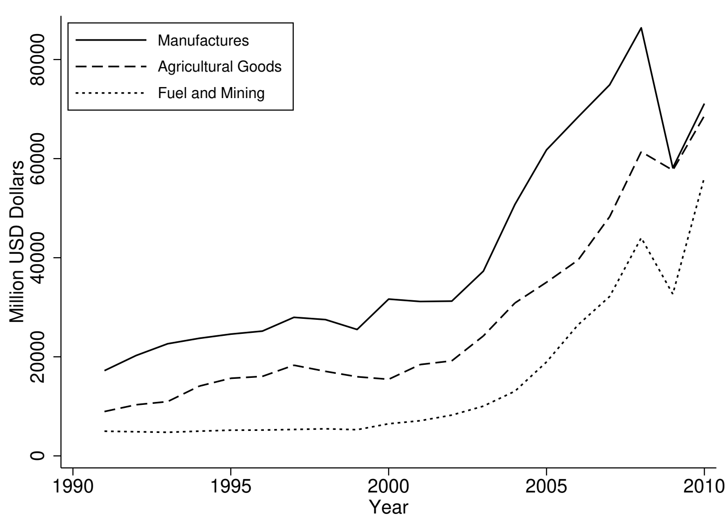
Appendix for Online Publication

A The Brazilian Economy

A.1 Brazilian Trade Patterns

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

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



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

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

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

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

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

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

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

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

A.2 Brazilian Economic Background and Informality

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

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

Table A.2: Exports by Products

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

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

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

In addition to informal employment, three further types of work are not reported in RAIS: self-employed workers, owner-managers who do not pay themselves a wage under Brazilian tax incentives, and unpaid workers because RAIS only reports work if it generates a formal wage payment. Figure A.2b shows the share of self-employed workers, employers and unpaid workers in Brazilian total employment. These three types of employment represented 30–40% of Brazilian employment in the 1990s and 2000s. We use the Brazilian Population Census in 1991, 2000, and 2010 to compare experience-wage profiles for Brazilian wage workers and self-employed workers. We estimate experience-wage profiles by applying the HLT method. Differing from the Mincer regressions estimated in Section 2.2, because we cannot identify the same individuals in multiple rounds of the Brazilian Population Census, we do not use the individual-level wage growth (we instead control for cohort effects of birth years). We apply the identical Mincer regression of wage levels as in Lagakos et al. (2018), with 10 years of no experience returns at the end of the working life and a 0% depreciation rate. As shown in Figure A.3b, we find that wage workers have steeper profiles than self-employed workers.

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

(a) Share of Informal Employees

(b) Share of Non-employees in Occupied Pop

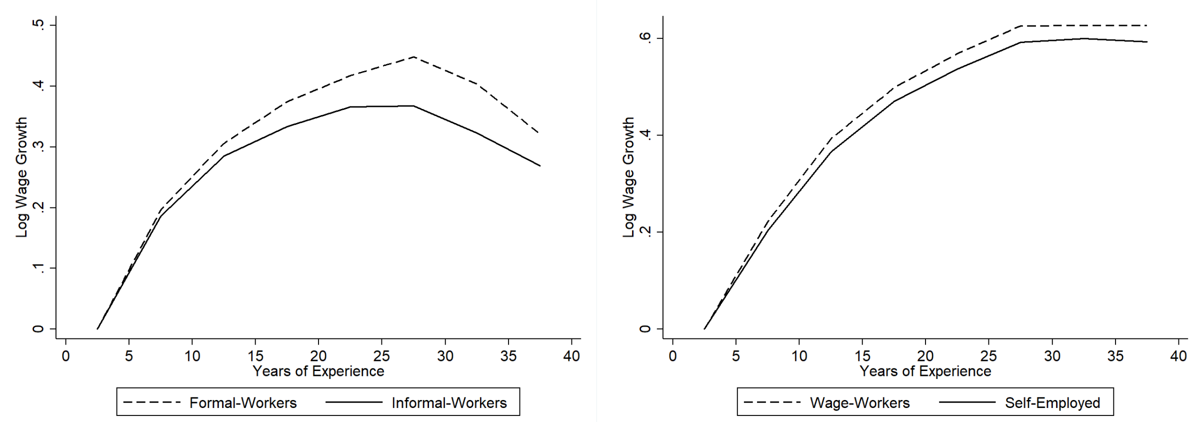
Notes: The left-hand figure shows the share of unregistered employees in total employees. In the right-hand panel, the share of self-employed people represents the ratio of the amount of self-employed workers to total occupied population. The share "+ employers" is the share of self-employed and employers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

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

B Description of the RAIS and Customs Data

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

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



(a) Informal and Formal Workers **(b)** Wage and Self-employed Workers

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

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

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

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

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

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

Table B.1: Sample Statistics

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

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

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

B.1 Summary Statistics

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

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

2000.[4]

B.2 A First Glance at Experience-Wage Profiles

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

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

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

There are many identification problems with this first-pass attempt: for example, workers observed at exporters in a given year may have previously accumulated work experience at non-exporters in their earlier career. Nonetheless, the preliminary evidence from the raw data indicates that workers at exporters may have steeper experience-wage profiles than workers at non-exporters. We formally estimate experience-wage profiles in Section 2.2.

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

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

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

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

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

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

C Empirical Method

C.1 HLT Method

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

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

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

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

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

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

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

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

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

C.2 Propensity Score Matching

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

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

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

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

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

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

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

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

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

D Additional Empirical Results

D.1 Industry Composition and Returns to Experience

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

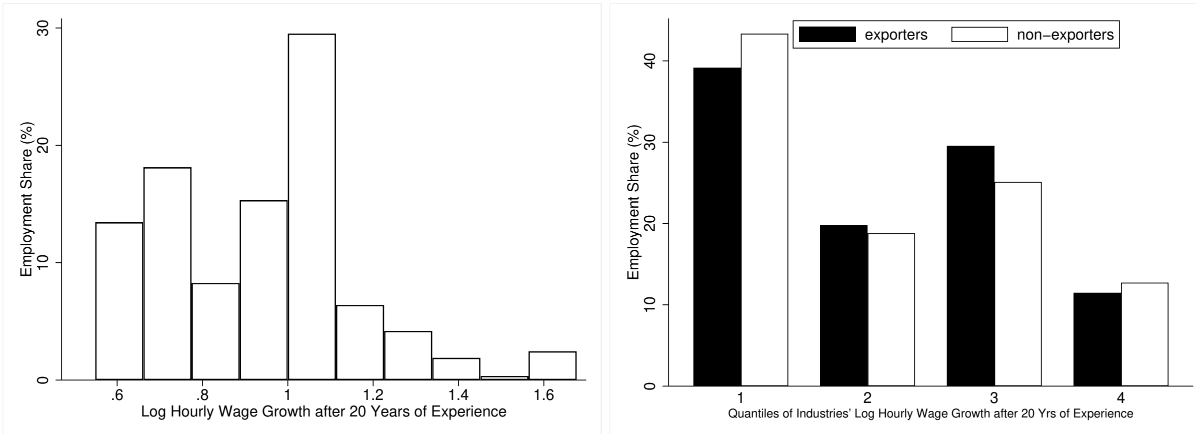
We first examine the role of industry composition in driving the difference of experience-wage profiles between exporters and non-exporters. We perform regression equation (1) separately for workers in each 3-digit manufacturing industry between 1994–2010. Figure D.1a illustrates the cross-industry distribution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

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

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

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

Figure D.1: Returns to Experience and Industry Heterogeneity



(a) Distribution of Log Hourly Wage Increase Across Industries

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

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

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

D.2 Robustness Checks of Table 1

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

D.3 Event Study

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

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

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

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

the following regression:

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

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

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

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

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

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

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

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

D.4 Propensity Score Matching Estimator

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

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

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

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

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

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

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

D.5 Case Study: Brazilian Currency Crisis 1999

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

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

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

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

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

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

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

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

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

D.6 Panel Estimation of Workers' Experience Effects

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

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

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

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

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

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

Column (1) of Table D.15 reports the estimation results. We do not report the returns to 21–25 years of experience, for which there are few observations and thus the estimates are noisy. The results show that returns to schooling are small, because after controlling individual fixed effects, identification of returns to education depends on within-individual changes in schooling over time (subject to large noises). Instead, a cross-sectional Mincer regression indicates that the return to education is 8.6% per year of schooling, in close accord with the literature (e.g., Young, 2013). More importantly, according to our estimation results, if a new worker with average schooling (9 years) starts her job at exporters, she enjoys a $-0.018 + 0.003 \times 9 = 0.9\%$ wage premium relative to a job at non-exporters. If she continues to work at exporters, her wage growth is 15 percentage points higher than working at non-exporters over 20 years of experience, in line with our estimation results in Section 2.2.

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

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

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

D.7 Tables and Graphs

Table D.1: Wage Profiles and Control Variables

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

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

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

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

Notes: This table presents estimates from regressions of firm-year-level returns to 20 years of experience on firm characteristics. The reference group is non-exporters. Controls: 1) average years of schooling; 2) share of workers with high-school degree; 3) share of occupations intensive in cognitive tasks; 4) share of production workers; 5) average worker age; 6) firm employment; and 7) firm employment percentiles (divided into 10 bins) within each industry-year bin. Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%. *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

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

	Dep Var: Firm-year-level Returns to 20 Yrs of Experience					
	(1)	(2)	(3)	(4)	(5)	(6)
Sample period	94–10	94–10	94–10	97–00	97–00	97–00
Exporter	0.238***	0.027	0.005	-0.073	-0.150	-0.121
	(0.018)	(0.041)	(0.049)	(0.094)	(0.167)	(0.165)
Exporter × ratio of # 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

Notes: This table presents estimates from regressions of firm-year-level returns to 20 years of experience on firm characteristics. The reference group is non-exporters. Controls: 1) average years of schooling; 2) share of workers with high-school degree; 3) share of occupations intensive in cognitive tasks; 4) share of production workers; 5) average worker age; 6) firm employment; and 7) firm employment percentiles (divided into 10 bins) within each industry-year bin. Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%. *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

Table D.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 × ratio of	0.006**	0.007***	0.002	0.004*	0.000	0.002	0.000	-0.001
#high-income to #total dests	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
Industry and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	344,658	344,658	344,658	344,658	312,083	295,140	305,180	242,661
R-squared	0.386	0.418	0.411	0.405	0.409	0.391	0.376	0.368

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

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

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

Notes: This table presents estimates from regressions of firm-year-level returns to 20 years of experience on firm characteristics. The reference group is non-exporters. Controls: 1) average years of schooling; 2) share of workers with high-school degree; 3) share of occupations intensive in cognitive tasks; 4) share of production workers; 5) average worker age; 6) firm employment; and 7) firm employment percentiles (divided into 10 bins) within each industry-year bin. Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%. We define the duration as follows. Duration of workers' previous experience at exporters: we compute each worker's duration of work history (before current year) at exporters and then take the average across all workers at the current firm in the current year. Duration of workers' previous experience at exporters (high-income dests): we compute each worker's duration of work history (before current year) at exporters that export to high-income destinations and then take the average across all workers at the current firm in the current year. Duration of firms' previous export participation: we compute the firm's duration of export participation (before current year). Duration of firms' previous export participation (high-income dests): we compute the firm's duration of export participation in high-income destinations (before current year). *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

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

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

Notes: This table presents estimates from regressions of firm-year-level returns to 20 years of experience on firm characteristics. Senior workers refer to workers in experience bins of 31–40 years, whereas young workers refer to workers in experience bins of 1–20 years. The reference group is non-exporters. Controls: 1) average years of schooling; 2) share of workers with high-school degree; 3) share of occupations intensive in cognitive tasks; 4) share of production workers; 5) average worker age; 6) firm employment; and 7) firm employment percentiles (divided into 10 bins) within each industry-year bin. Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%. *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

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

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

Notes: This table presents estimates from regressions of firm-year-level returns to 20 years of experience on firm characteristics. The reference group is non-exporters. Because unit prices are not directly comparable across products, we first compute firms' unit prices of products relative to average unit prices of exports to Argentina (which is of similar development levels to Brazil) for each 8-digit product and year. We then use export volume as weights to compute a weighted average unit price of exports for each firm and year. Controls: 1) average years of schooling; 2) share of workers with high-school degree; 3) share of occupations intensive in cognitive tasks; 4) share of production workers; 5) average worker age; 6) firm employment; and 7) firm employment percentiles (divided into 10 bins) within each industry-year bin. Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%. *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

Table D.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

Notes: This table presents regressions of firm-year-level returns to 20 years of experience on firm characteristics. The reference group is non-exporters. Controls: 1) average years of schooling; 2) share of workers with high-school degree; 3) share of occupations intensive in cognitive tasks; 4) share of production workers; 5) average worker age; 6) firm employment; and 7) firm employment percentiles (divided into 10 bins) within each industry-year bin. Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%. *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms in Columns (1)–(5) and agricultural and mining firms in Column (6).

Table D.9: Wage Profiles and Control Variables

	Dep Var: Firm-year-level Returns to 20 Yrs of Experience									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Sample period	94–10	94–10	94–10	94–10	94–10	94–10	94–10	94–10	94–10	94–10
Exporter	-0.015	-0.013	-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 occupations intensive in cognitive tasks								-0.038		
×ratio of #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

Notes: This table presents estimates from regressions of firm-year-level returns to 20 years of experience on firm characteristics. Controls: 1) average years of schooling; 2) share of workers with high-school degree; 3) share of occupations intensive in cognitive tasks; 4) share of production workers; 5) average worker age; 6) firm employment; and 7) firm employment percentiles (divided into 10 bins) within each industry-year bin. Due to the space constraint, we do not report the coefficient on the interaction between the control variable and the exporter dummy, which is statistically insignificant in all scenarios. We also control for the levels of control variables when the corresponding interaction term is included. The reference group is non-exporters in the upper 10% of firm employment distribution within each industry-year. Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%. *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

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

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

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

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

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

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

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

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

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

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

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

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

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

Dep Var: Firm-year-level Log Hourly Wage Increase Time	(1) 1998-2000	(2) 1997-2001	(3) 1996-2002
Exporter × DV	-0.024	-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

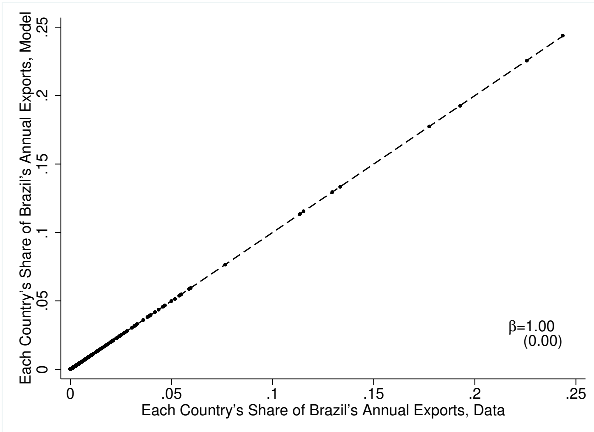
Notes: This table presents estimates from equation (D.2). The dependent variable is firm-year-level returns to 20 years of experience. The regression includes firm, industry, and year fixed effects. Controls: 1) average years of schooling; 2) share of workers with high-school degree; 3) share of occupations intensive in cognitive tasks; 4) share of production workers; 5) average worker age; 6) firm employment; and 7) firm employment percentiles (divided into 10 bins) within each industry-year bin. Robust standard errors in parentheses. Significance levels: * 10%, ** 5%, *** 1%. *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

Table D.15: Wage Determinants

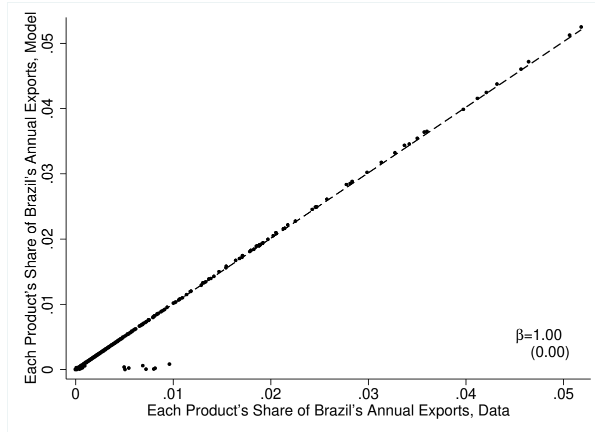
Dependent Variable: Log Hourly Wage (Current Year)	All Young Workers			Displaced Young Workers		
	(1)	(2)	(3)	(4)	(5)	(6)
Schooling	-0.001***	0.001***	-0.001***	0.059***	0.059***	0.059***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Schooling × Exporter	0.003***	0.003***	0.003***	0.023***	0.023***	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

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

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



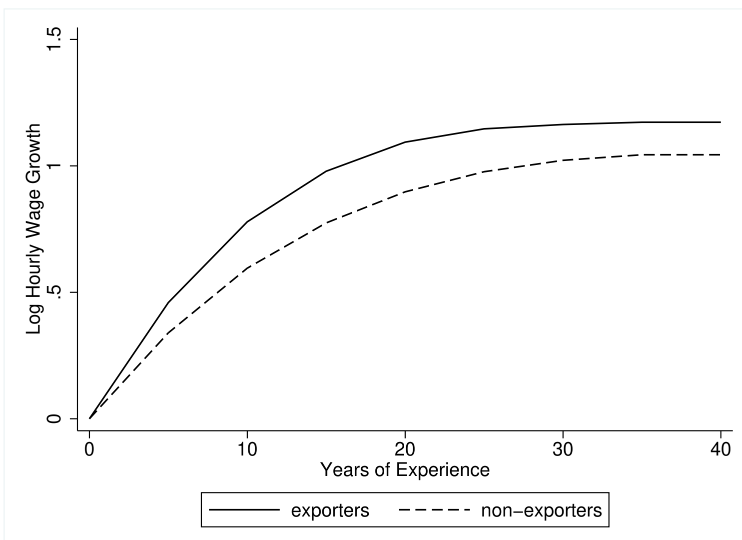
(a) Exports by Country



(b) Exports by 8-digit Products

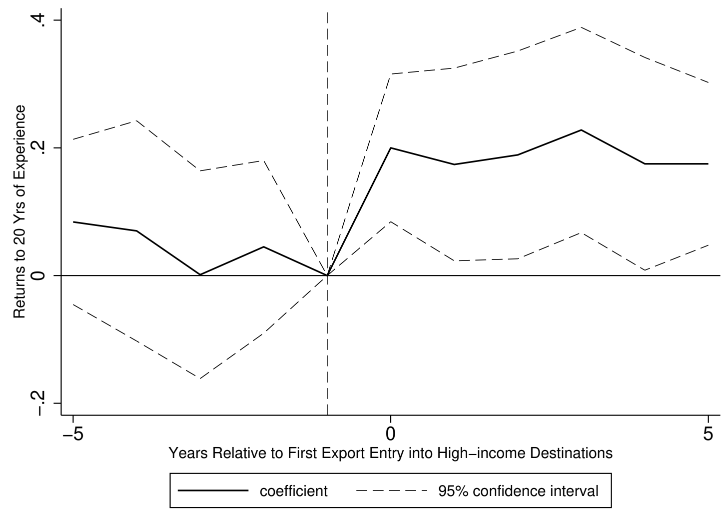
Notes: This graph compares each country's (product's) share of Brazilian annual exports between our SECEX customs data and the officially reported data from the Brazilian Ministry of Economy (Ministério da Economia). We pool the different years' shares together in the graph.

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



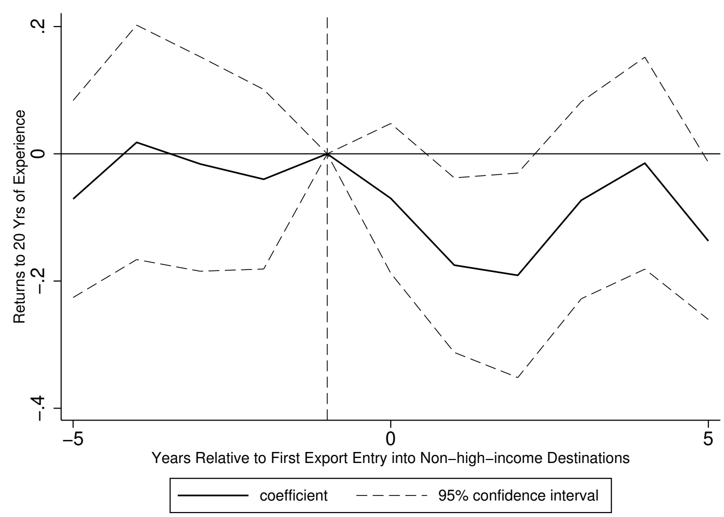
Notes: This figure presents the experience-wage profiles for workers at exporters and non-exporters, from estimating equation (1) using the Brazilian data between 1994–2010. We assume the final 5 years with no experience returns. *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted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

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



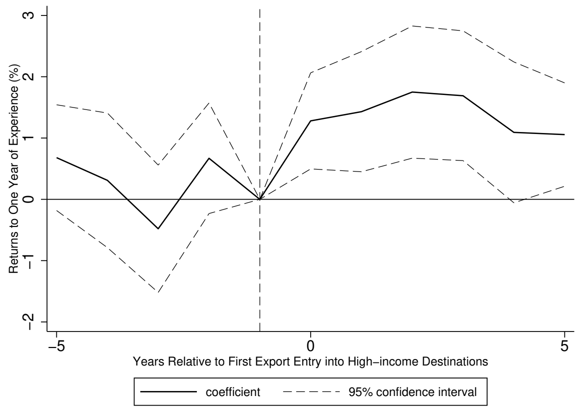
Notes: The figure shows the β_τ parameters from estimating equation (D.1). The dependent variable is firm-year-level returns to 20 years of experience. The regression controls for firm fixed effects, industry fixed effects, year fixed effects, and a dummy variable indicating whether the firm is exporting to a non-high-income destination. Other controls: 1) average years of schooling; 2) share of workers with high-school degree; 3) share of occupations intensive in cognitive tasks; 4) share of production workers; 5) average worker age; 6) firm employment; and 7) firm employment percentiles (divided into 10 bins) within each industry-year bin. To estimate the β_τ parameters after entry, we require that firms remain exporting to high-income destinations. *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

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

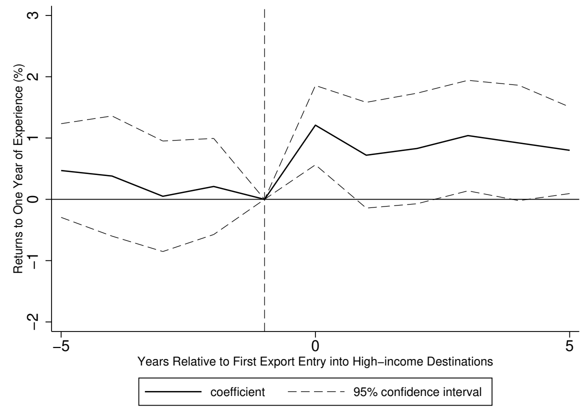


Notes: The figure shows the β_τ parameters from estimating equation (D.1), except for that the β_τ parameters are coefficients on indicators for time periods relative to the firm's first export entry into non-high-income destinations. The dependent variable is firm-year-level returns to 20 years of experience. The regression controls for firm fixed effects, industry fixed effects, year fixed effects, and a dummy variable indicating whether the firm is exporting to a high-income destination. Other controls: 1) average years of schooling; 2) share of workers with high-school degree; 3) share of occupations intensive in cognitive tasks; 4) share of production workers; 5) average worker age; 6) firm employment; and 7) firm employment percentiles (divided into 10 bins) within each industry-year bin. To estimate the β_τ parameters after entry, we require that firms remain exporting to non-high-income destinations. *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

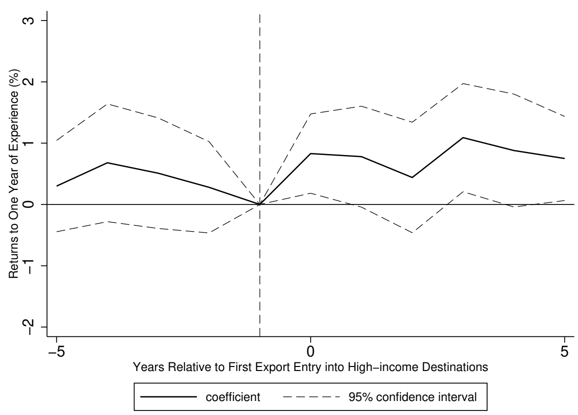
Figure D.6: Returns to One Year of Experience Across Different Experience Bins



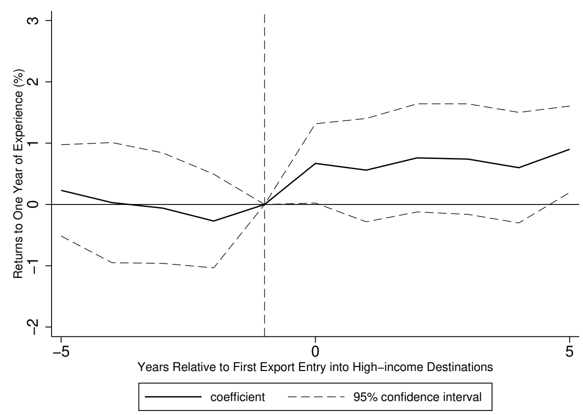
(a) Workers with 1–5 Years of Experience



(b) Workers with 6–10 Years of Experience



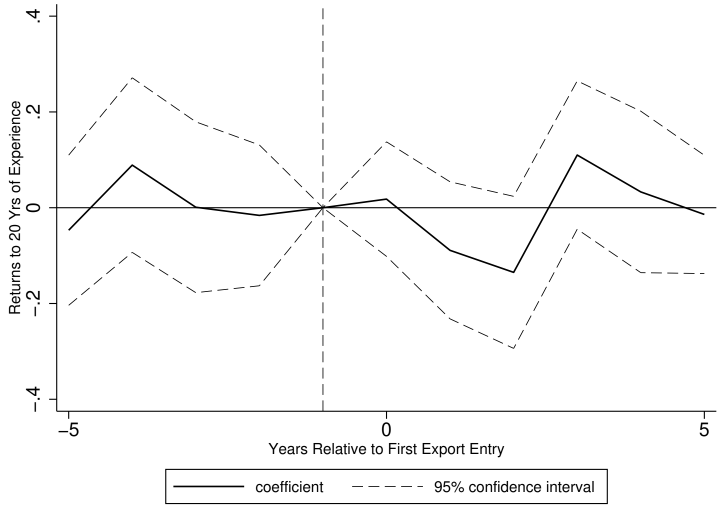
(c) Workers with 10–15 Years of Experience



(d) Workers with 16–20 Years of Experience

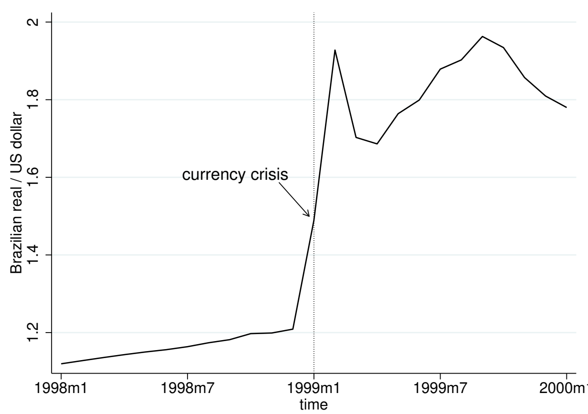
Notes: Parameters β_τ from estimating equation (D.1). The dependent variable is firm-year-level returns to one year of experience in the corresponding experience bin. Controls: firm fixed effects, industry fixed effects, year fixed effects, and an indicator for exports to a non-high-income destination. Other controls: 1) average years of schooling; 2) share of workers with high-school degree; 3) share of occupations intensive in cognitive tasks; 4) share of production workers; 5) average worker age; 6) firm employment; and 7) firm employment percentiles (divided into 10 bins) within each industry-year bin. To estimate the β_τ parameters after entry, we require that firms remain exporting to high-income destinations. *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

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

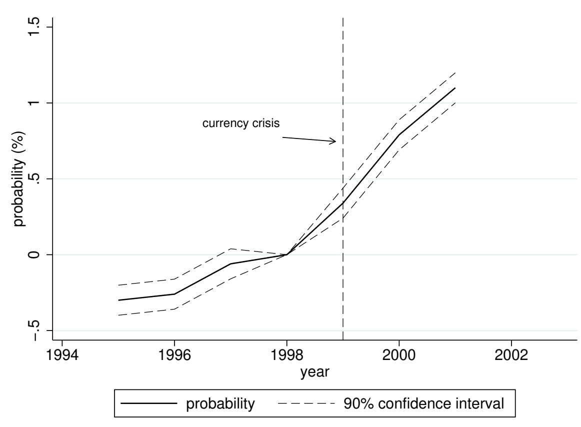


Notes: The figure shows the β_τ parameters from estimating equation (D.1), except for that the β_τ parameters are coefficients on indicators for time periods relative to the firm's first export entry. The dependent variable is firm-year-level returns to 20 years of experience. The regression controls for firm fixed effects, industry fixed effects, and year fixed effects. Other controls: 1) average years of schooling; 2) share of workers with high-school degree; 3) share of occupations intensive in cognitive tasks; 4) share of production workers; 5) average worker age; 6) firm employment; and 7) firm employment percentiles (divided into 10 bins) within each industry-year bin. To estimate the β_τ parameters after entry, we require that firms remain exporting. *Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

Figure D.8: Brazil Currency Crisis and Exporting Probability



(a) Brazil Currency Crisis



(b) Exporting Probability

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

E Additional Theoretical Results

E.1 Learning Function

The learning function (6)

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

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

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

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

E.2 Value of Employment and Job Value

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

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

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

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

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

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

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

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

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

E.3 Vacancy Choices

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

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

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

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

E.4 Definition of Equilibrium

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

Definition 1 *The general equilibrium consists of meeting rates $\{\lambda_E, \lambda_U\}$, employment distributions $\{D_U^a(h^a), D^a(h^a, \omega)\}$, firms' export destinations and revenues $\{y_n(\omega), \tilde{z}(\omega)\}$ and vacancy posting $v(\omega)$, the law of motion for a firm's state $\Gamma(\mathbf{x}(\omega))$, the worker-firm joint decision of human capital accumulation $s^a(h_i^a, \omega)$, each worker's piece rate $r_i(\omega)$, and aggregate price and quantity variables in the home country $\{P_1, Y_1\}$. These variables satisfy:*
(1) each worker's piece rate $r_i(\omega)$ satisfies the bargaining processes specified in Section 3.2.1;
(2) the worker-firm joint decision of human capital accumulation $s^a(h_i^a, \omega)$ is given by equation (9), which maximizes the job value specified by equation (E.2);
(3) firms' export destinations and revenues $\{y_n(\omega), \tilde{z}(\omega)\}$ are given to maximize the benefit in equation (10), given employment distributions and aggregate price and quantities, and the perceived law of motion for firms' state $\mathbf{x}'(\omega) = \Gamma(\mathbf{x}(\omega))$ is consistent with actual transition of firms' state over time;
(4) firms' optimal vacancy postings $v(\omega)$ are given by equation (E.3);
(5) meeting rates $\{\lambda_E, \lambda_U\}$ are determined by unemployment rate $U = \sum_a \int D_U^a(h^a)\, dh^a$ and the total amount of vacancies $V = \bar{M} \int v(\omega)\, d\Phi(z(\omega))$;
(6) employment distributions $\{D_U^a(h^a), D^a(h^a, \omega)\}$ are consistent with revenues $\tilde{z}(\omega)$, vacancies $v(\omega)$, and the worker-firm joint decision of human capital accumulation $s^a(h_i^a, \omega)$ across all workers within the firm $i \in \mathbb{I}(\omega)$; and
(7) aggregate price and quantity $\{P_1, Y_1\}$ clear the goods market in the home country.

E.5 Decomposition of Gains from Trade

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

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

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

[22] This assumption can be justified by $z_{\text{min}} \to 0$ or disutility of unemployment (Hornstein et al., 2011), though in the current model's quantitative analysis, we abstract from directly modeling the unemployment disutility by following Bagger et al. (2014) to conveniently assume that the unemployment value is equivalent to the employment value in the least productive firm, as discussed in Section 3.2.

gains from trade are:

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

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

Proof: See Section E.6. □

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

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

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

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

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

E.6 Proof of Proposition 1

E.6.1 Optimal quantities sold to export destinations

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

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

We can redefine the problem as:

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

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

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

Solving these first-order conditions leads to:

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

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

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

E.6.2 Optimal hires and export choices

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

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

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

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

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

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

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

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

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

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

which is identical across firms.

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

E.6.3 Trade shares in the home market

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

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

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

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

E.6.4 Gains from trade

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

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

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

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

This step completes the proof.

E.7 Incorporating Learning-by-Doing

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

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

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

F Additional Quantitative Results

F.1 Computation Algorithm

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

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

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

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

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

F.2 Moments and Model Validation

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

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

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

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

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

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

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

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

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

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

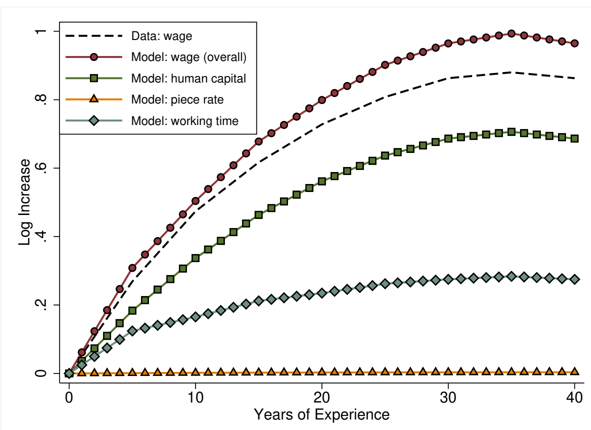
[26]For example, in the 1995 U.S. Survey on Employer-provided Training, firms with 50–99 employees only report 21% of their training time as formal training, whereas firms with 500+ employees report 40% of their training time as formal training.

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

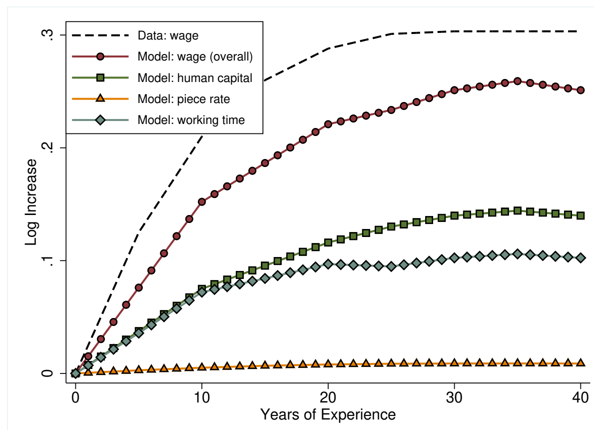
Dep Var	Log(% of trained workers)		Log(time on HC accumulation)	
	data	data	model	model
Log(avg firm employment)	0.209***	0.192***	0.104***	0.083***
	(0.029)	(0.062)	(0.010)	(0.025)
Share of exporters		0.116		0.045
		(0.380)		(0.049)
Obs	50	50	50	50
R-squared	0.626	0.626	0.839	0.844

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

Figure F.1: Decomposing the Returns to Experience



(a) Overall Experience-wage Profiles



(b) Difference btw Exporters/non-exporters

Notes: The data on experience returns are computed according to Section 2.3. We report the (unweighted) average experience-wage profiles across firms in Figure F.1a and the (unweighted) average differences between exporters and non-exporters in Figure F.1b. *Data Sources*: RAIS employer-employee and SECEX customs data, 1994–2010, restricted to manufacturing firms.

F.3 Decomposing the Returns to Experience

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

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

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

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

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

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

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

F.4 Robustness Checks of Quantitative Model

F.4.1 Alternative parameterization

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

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

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

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

Table F.4: Robustness Checks

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

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

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

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

F.4.2 Model with learning-by-doing

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

[28] As shown in Section 3.2, if the joint surplus of the job at poaching firms is higher than workers' current value but lower than the joint surplus of the current job, workers' value will increase to the joint surplus of the job at poachers, even though they could not get a share of the difference in the joint surplus between poachers and the current firm because of $\beta = 0$. Because workers start with low bargaining positions, the difference between workers' value and the joint surplus of the job at the current firm is large.

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

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

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

The last row in Table F.4 reports that the gains in human capital from trade are 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, work time is upward sloping over the life cycle. This upward trend in work time over the life cycle would naturally explain a portion of experience-wage profiles. Thus, compared with the LBD model, our baseline model attributes a smaller portion of lifetime wage profiles to human capital growth, thus leading to a more conservative assessment about the role of human capital in shaping the gains from trade.

F.5 Role of Labor Market Frictions

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

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

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

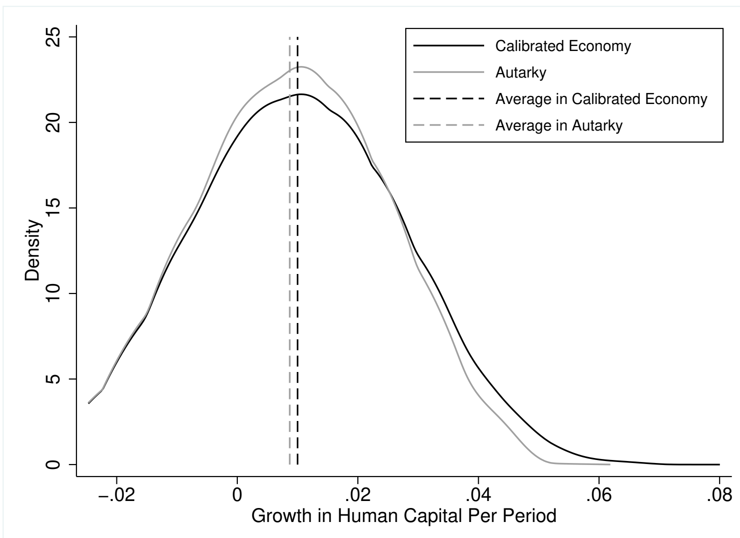
G Additional Tables and Graphs

Table G.1: Identification of Parameters γ_1 and γ_2

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

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

Figure G.1: Distribution of Human Capital Growth



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

Appendix References

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