IZA Institute of Labor Economics
Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 10718

Skill Premium, Labor Supply and Changes in the Structure of Wages in Latin America

Manuel Fernández
Julián Messina

APRIL 2017

I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 10718

Skill Premium, Labor Supply and Changes in the Structure of Wages in Latin America

Manuel Fernández
University of Oxford

Julián Messina
Inter-American Development Bank and IZA

APRIL 2017

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Skill Premium, Labor Supply and Changes in the Structure of Wages in Latin America*

Earnings inequality declined rapidly in Argentina, Brazil and Chile during the 2000s. A reduction in the experience premium is a fundamental driver of declines in upper-tail (90/50) inequality, while a decline in the education premium is the primary determinant of the evolution of lower-tail (50/10) inequality. Relative labor supply is important for explaining changes in the skill premiums. Relative demand trends favored high-skilled workers during the 1990s, shifting in favor of low-skilled workers during the 2000s. Changes in the minimum wage, and more importantly, commodity-led terms of trade improvements are key factors behind these relative skill demand trends.

JEL Classification: E24, J20, J31

Keywords: earnings inequality, unconditional quantile regressions, supply-demand framework, human capital

Corresponding author:
Julián Messina
Research Department
Inter-American Development Bank
1300 New York Avenue, NW
Washington, DC 20577
USA
E-mail: julianm@iadb.org

* Authors would like to thank Joao Pedro Azevedo, Brian Bell, Climent Quintana-Domeque, Simon Quinn and seminar participants at The World Bank and Oxford University for helpful comments and suggestions. The views expressed in this article are those of the authors and not those of the Inter-American Development Bank.

1 Introduction

Inequality declined sharply in Latin American countries after the turn of the century, a contrast with its own history and global trends (Ferreira et al., 2008; Kahhat, 2010; López-Calva and Lustig, 2010; Gasparini and Lustig, 2011; Gasparini et al., 2011; Levy and Schady, 2013; Lustig et al., 2013). Redistribution through progressive fiscal policy, the emergence of conditional cash transfer programs for the poor, and changes in household demographics played a role in this transition. However, a broad conclusion of previous literature is that the key contribution to inequality reduction was the decline in earnings inequality (Lopez-Calva and Lustig, 2010; Azevedo et al., 2013). Earnings inequality declined in 16 of the 17 countries in Latin America for which consistent statistics can be calculated (Messina and Silva, 2016), although the intensity and turning points diverged across countries. For example, after a decade of stagnant or slowly increasing inequality, the 90th/10th interquartile range of the labor earnings distribution declined by 20 percent in Argentina and 28 percent in Chile between 2000 and 2013. In Brazil, where earnings inequality started to fall as early as 1990, the reduction has been a remarkable 46 percent since the year 2000.

There is a relatively extensive literature examining the forces behind increasing inequality in Latin American countries during the 1980s and early 1990s. Trade is often mentioned as a driving force for the inequality increase in Argentina, Brazil, Chile and Mexico (Goldberg and Pavcnik, 2007; Galiani and Sanguinetti, 2003; Green et al., 2001; Pavcnik, 2003; Robertson, 2004). The literature examining the forces behind the recent inequality decline is much less extensive, and it concludes that traditional trade channels are unlikely to account for a significant fraction of the observed trends. Adao (2015) focuses on shocks due to commodity prices and finds that they can account for only 5 to 10 percent of the fall of earnings inequality in Brazil. Also for Brazil, Costa et al. (2016) examine the local labor market effects of import penetration of manufacturing goods and increasing demand for commodities from China and find that, if anything, the overall impact on inequality was mildly positive. Similarly, Halliday et al. (2015) show that the fall of earnings inequality in Mexico that started in 1995 is inconsistent with traditional trade models.

An often overlooked aspect is that most countries in the region registered a rapid transformation in the age, education and gender composition of their labor forces. Between 1990 and 2013, the share of college-educated workers increased from 16.6 to 26.6 percent in Argentina, virtually doubled in Chile (14.3% to 27.7%) and almost tripled in Brazil (7.5% to 19.5%). The average worker age increased by more than a year in Argentina (37.3 to 39.0), by three years in Brazil (34.1 to 37.4), and by more than four years in Chile (35.8 to 40.4). The share of females in the labor force increased in all countries with Brazil and Chile ahead of the pack: an increase of more than 8 percentage points. Changes in the composition of the labor force can mechanically affect wage inequality because different types of workers have different levels of within-group wage dispersion (Lemieux, 2006). They can also affect inequality by changing between-group differences in pay, as suggested by the seminal paper of Katz and Murphy (1992) and numerous applications of a simple supply-demand framework to account for changes in the education premium in the US.

This paper investigates how these changes in the demographic and skill structure of the labor force influenced the evolution of the distribution of earnings in Argentina, Chile and Brazil during the last 25 years using household survey data. Our analysis starts by distinguishing the contribution of pure composition changes from changes in the structure of pay. Following the work of Firpo et al. (2007, 2009) we construct counter-factual wage distributions that decompose the observed changes in inequality measures into price and composition effects. The analysis distinguishes between overall inequality and inequality at the bottom and top of the distribution of earnings. This is important because trends have been different. While most of the reduction in earnings inequality in Brazil was the result of a decline in the 50th/10th interquartile range (-31% since 2000), the reduction in inequality in Argentina was mostly driven by a fall of the 90th/50th interquartile range (-23% since 2000). In Chile, inequality fell symmetrically at the bottom and at the top of earnings distribution (-15% since 2000).

We find that falling education and labor market experience premiums are key determinants of the observed changes in inequality. By contrast, the increasing incorporation of women into the labor force had small effects. The declining experience premium had a larger explanatory power in the reduction of inequality in the upper half of the distribution. In contrast, the decline of the returns to schooling explains a larger share of inequality reduction at the bottom. Against these dominating patterns, pure composition changes related to the increase in educational attainment were inequality enhancing, thus contributing to increasing inequality in the early 1990s in Argentina and Chile but working against the recent inequality decline. This may be due to within-group differences in pay as highlighted by Lemieux (2006) in the US, or may reflect a phenomenon previously labeled as the paradox of progress (Bourguignon et al., 2005a), by which increases in educational attainment can be inequality-increasing due to convexity of the returns to education.

Our analysis continues by assessing the role of the aforementioned labor supply changes in the observed education and experience premiums. Have declines in those premiums been driven by increasing educational attainment and aging of the labor force? Following the seminal work of Katz and Murphy (1992), Murphy and Welch (1992) and Card and Lemieux (2001), we build a stylized model of supply and demand for labor in which workers with different skills are imperfect substitutes in production. We then use household-level data from Argentina, Chile and Brazil to estimate the parameters of the model and to derive implications for the role of supply and demand factors in the evolution of experience and education premiums.

We show that a combination of imperfect substitutability between skill groups and the observed movements in relative supplies goes a long way towards explaining the changes in relative returns, especially the declines of both the schooling and experience premiums. Most of the fall in the high school/primary schooling premiums, which we find is a significant factor behind the decline in lower-tail inequality in these countries, can be accounted for by the significant increase of workers with at least a high school degree. According to our model, the observed changes in labor supply should have resulted in an even greater reduction of the high school premium than the observed one, especially during the 1990s. This is because the demand for high school-educated workers increased in this period. The picture for college-educated workers is slightly different. We show that the rising supply of college-educated workers has also pushed the college premium downwards over the past 25 years. However, relative demand trends did not increase steadily, as was the case for high school graduates. Relative demand favored college-educated workers during the 1990s but started declining at the start of the new millennium. The implication is that demand-side trends attenuated labor supply forces towards a declining college premium during the 1990s, but accentuated the decline after 2003. In other words, the demand for college-educated workers followed an inverse U-shaped pattern that peaked in 2003.

Further, we show that changes in the educational premiums are not the only factors driving the reconfiguration of the wage structure. The experience premiums also declined substantially to contribute to the inequality reduction, especially within groups of workers with similar levels of schooling. We provide novel estimates in the region for the elasticities of substitution between workers with different experience levels. These estimates suggest that aging of the workforce has contributed to changes in the experience premium, and through this channel to changes in inequality.

The supply-demand model used in the second part of the paper is closely related to the framework developed by Manacorda et al. (2010) (henceforth MSPS) to analyze changes in the skill premium in Latin America during the 1990s. We depart from MSPS in two significant ways. First, our model allows for imperfect substitutability across experience groups within schooling levels. We show that this distinction is empirically relevant. MSPS finds workers of different age groups to be perfect substitutes in production, a feature rejected by the data in our model. Second, we extend the model to allow for differential demand trends across education and experience groups, which is crucial for rationalizing the data. Our estimates suggest that relative demand favored more educated and experienced workers during the 1990s, but that there was a shift around the 2000s. Beyond these two extensions we reinforce the call in MSPS for differentiating between workers with secondary schooling and those with at most primary education when thinking about labor market outcomes in Latin America. In line with MSPS, our evidence suggests these two groups are not perfect substitutes in production.

The paper concludes by discussing a number of robustness checks and extensions. In particular, we assess what forces may be behind the trend reversal in the demand for high-skilled workers. Real minimum wages increased dramatically during the 2000s in the three countries. This could compress the skill premium by boosting wages of low-skilled workers. Our findings suggest that they had a role in Brazil and Chile, but declining demand for high-skilled workers after 2003 persists after controlling for the evolution of the minimum wage. Other factors including changes in aggregate labor market conditions as represented by changes in the unemployment rate, and above all the rapid terms of trade improvement boosted by rapidly increasing commodity prices had a significant role in the reversal of skills demand.

The rest of the paper is organized as follows. Section 2 discusses the data and main stylized facts, reviewing the evolution of inequality and socio-demographic changes in Argentina, Brazil and Chile. Section 3 shows how changes in inequality were affected by compositional changes and changes in the wage structure associated with education, experience and gender. In Section 4 we develop a simple stylized model of supply and demand based on the descriptive trends in the data, and Section 5 provides estimates to the key parameters of the model and discusses its implications for the evolution of the skill premium. We provide several extensions and robustness exercises that aim at understanding the sensitivity of our results to the modeling choices in Section 6. Finally, Section 7 concludes.

2 Data and Stylized Facts

Household surveys for Argentina, Brazil and Chile are used for the analysis. All surveys include information about general characteristics of the workers (e.g., gender, age, education) and their jobs (type of contract, labor earnings, hours worked). With the exception of Argentina, where information is restricted to urban areas,[1] all other surveys are nationally representative. Earnings refer in the three surveys to total monetary payments from labor in a reference period. Labor earnings are divided by actual worked hours during the same period to obtain hourly earnings. The series are converted into real terms using the Consumer Price Index (CPI).[2] We restrict the sample to individuals between the ages of 16 and 65[3] and only use earnings of full-time workers (individuals that self-reported working for more than 35 hours in the reference week[4]). For further details on the characteristics of the surveys and the construction of the variables see Appendix A.2.

Earnings inequality as summarized by the 90/10 log wage differential declined during the 2000s,[5] reversing the increasing trend documented for the 1980s and the first years of the 1990s (Figure 1).[6] The reversal of the trend started at different years in our sample of countries, with peaks around 1996

[1]Urban areas account for almost 90 percent of the total population in the Argentina in 2013.

[2]The official CPI is used in Brazil and Chile. Due to inconsistencies found in the official series in Argentina (see Cavallo (2013)), we use the information from PriceStats (`http://www.statestreet.com/ideas/pricestats.html`) instead. Because the paper focuses on inequality, the use of the price deflator does not make a significant difference in the results.

[3]We show in the robustness section of the paper that our main results are unchanged if we restrict the sample to prime-age workers (between 25 and 55 years of age).

[4]The average share of workers that reported working less than 35 hours per week is 15 percent in Chile and Brazil, and close to 28 percent in Argentina. We present alternative estimates of our main results including part-time workers in the robustness section of the paper.

[5]See also Ferreira et al. (2008); Kahhat (2010); López-Calva and Lustig (2010); Gasparini and Lustig (2011); Gasparini et al. (2011); Levy and Schady (2013); Lustig et al. (2013).

[6]See Cragg and Epelbaum (1996); Londoño and Szekely (2000); Sanchez-Paramo and Schady (2003); Behrman et al. (2007); Cornia (2010); Manacorda et al. (2010) among others.

in Chile and 2002 in Argentina. Inequality in Brazil declined steadily during our period of analysis that starts in 1990. The contraction of the earnings distribution is quite significant. Since the year 2000, the ratio between the 90th and 10th percentiles contracted by 20 percent in Argentina, 28 percent in Chile, and a remarkable 46 percent in Brazil. Nonetheless, the levels of earnings inequality remain among the highest in the world in 2013. The 90/10 log earnings ratio was close to 1.7 in the three countries, implying that the hourly earnings of a worker at the 90th percentile of the distribution is more than 5.5 times what a worker at 10th percentile gets. As a point of comparison, the OECD average of the 90/10 interdecile ratio in 2012 was 4.[7]

In the three countries we observe a drop in both the 90/50 and 50/10 log wage ratio after inequality peaked. This contrasts with a large body of literature from developed countries that shows that most of the changes in the wage structure have taken place at the top of the income distribution.[8] With the exception of Argentina, which displays a small increase in the 50/10 log wage ratio since the initial levels of 1995, the recent decline of all inequality measures have brought inequality below the levels of the early 1990s.

These changes in the distribution of earnings are taking place when the skill and demographic composition of the workforce is also changing significantly. Major shifts include changes in the education, experience and gender composition of the labor force. The percentage of workers with a primary education degree in the early 1990s was 47.2 percent in Argentina, 49.3 percent in Chile, and 77 percent in Brazil.[9] By 2013 that share had dropped in a range from 17.7 percentage points in Argentina to 34.3 percentage points in Brazil (Table 1). The gains in schooling are reflected in an increase of the share of workers with high school education completed, as well as by an increase in the share of workers with a college degree. For example, the share of college-educated workers increased from 16.5 to 26.6 percent in Argentina, almost doubled in Chile (14.3% to 27.7%), and almost tripled in Brazil (7.5% to 19.5%).

The average age of a worker increased by more than a year in Argentina (37.3 to 39), three years in Brazil (34.1 to 37.4), and four years in Chile (35.8 to 40.4). Even with the sharp rise in the levels of schooling, this demographic

[7]See `http://stats.oecd.org/`.

[8]See Katz and Autor (1999); Autor et al. (2005, 2008); Lemieux et al. (2009); Acemoglu and Autor (2011) and the references therein.

[9]See Appendix A for details on the aggregation of workers with incomplete levels of schooling.

shift has resulted in a rise in the average level of potential experience.[10] This is especially significant in the case of Chile, were the share of workers with more than 20 years of potential experience increased by 11.9 percentage points.

In the early 1990s female labor force participation was as low as 35 percent in Chile and close to 50 percent in Argentina and Brazil. By 2013 half of the women between the ages of 16 and 65 in Chile where working, and female labor force participation in Argentina and Brazil was close to 60 percent. As a consequence of this shift, the employment share of women rose by more than 8 percentage points in Brazil and Chile.

3 Inequality, Workforce Compositional and Wage Structure

Changes in the composition of the labor force will affect inequality across and within labor market skill groups. Perhaps the most studied characteristic is education. Facilitating access to education to the poor is a powerful tool for social mobility and may lead to lower inequality in the long run. However, because the education premium is convex, in the short and medium term educational upgrading may increase between-group inequality. This "paradox of progress" (Bourguignon et al., 2005b) may occur even when changes in educational attainment are moderately in favor of low socio-economic background groups, and was recently confirmed for several Latin American countries by Battistón et al. (2014). Moreover, within-group dispersion is typically much higher among highly educated workers, pushing inequality up when educational attainment increases (Lemieux, 2006).

The role of composition changes associated with labor market experience and gender on inequality is less straightforward. Returns to experience are concave (Murphy and Welch, 1990), a force that would push between-group inequality down when the labor force is aging. However, within-group wage dispersion is higher among high-experience workers than among their low-experienced counterparts, possibly limiting the inequality decline (Lemieux, 2006). Similarly, the importance of composition effects associated with gender depends on the skills distribution of the women that are increasingly accessing the labor market.

A simple decomposition exercise can help disentangle the importance of composition and price effects on inequality. The idea is to exogenously fix the

[10] We define potential experience as: age-years of education-6.

structure of relative wages at the average level across the last two decades and quantify the counterfactual levels of the interquantile wage ratios under the observed compositional changes. Alternatively, we can keep the composition of the labor force fixed at a given point in time and construct counterfactual wage distributions to evaluate how changes in the schooling, experience and male premiums have affected the observed inequality dynamics.

The decomposition we propose follows Firpo et al. (2007, 2009), which have recently shown that using the properties of Recentered Influence Functions (RIF) one can extend the traditional Oaxaca-Blinder decomposition to analyze distributional statistics beyond the mean (e.g., quantiles). Details on the method are found in the Appendix A.3. As a starting point, consider a transformed wage-setting model of the form

$$RIFq_{\tau t} = X_t'\gamma_t + \epsilon_t \text{ for } t = 1, 0, \tag{3.1}$$

where t identifies the initial ($t = 0$) and final ($t = 1$) periods; $RIFq_{\tau t}$ represents the value of the RIF corresponding to the τ'th quantile of the earning distribution at time t; X is a vector of socio-demographic characteristics including quadratic terms in education and experience and a female dummy.[11] We can estimate equation (3.1) by OLS, and we express the estimated difference over time of the expected value of the wage quantile $\hat{q}_\tau$ as

$$\Delta\hat{q}_\tau = \underbrace{\left(\overline{X'}_1 - \overline{X'}_0\right)\hat{\gamma}_P}_{\Delta\hat{q}_{X,\tau}} + \underbrace{\overline{X'}_P\left(\hat{\gamma}_1 - \hat{\gamma}_0\right)}_{\Delta\hat{q}_{S,\tau}}, \tag{3.2}$$

where overbars denote averages, and $\hat{\gamma}_P$ and $\overline{X}_P$ correspond to the estimated vectors of parameters and the explanatory variables of a wage-setting model in which observations are pooled across the two periods.[12] Here, $\hat{q}_{X,\tau}$ corresponds to the composition effect, which captures the part of the change in the τ'th wage quantile that is accounted for by changes in the average skill-demographic

[11] As in the Oaxaca-Blinder decomposition for the mean, this decomposition is not invariant to the reference variable chosen when covariates are categorical. We limit this problem by using quadratic polynomials in years of education and potential experience. In the case of gender, we repeated the decomposition with a male dummy and a female dummy. The results were qualitatively similar.

[12] This specific counterfactual allows us to analyze composition and wage structure effects relative to a baseline defined by both the (weighted) mean returns and (weighted) mean characteristics over the two periods.

characteristics of the workforce, given that we set the skill returns at their (weighted) average over the two periods; and $\hat{q}_{S,\tau}$ is the wage structure effect, and captures how changes in returns are affecting wages at the quantile τ, given that the observable characteristics are fixed to be equal to their (weighted) average over time.

Since we are interested in the effects of compositional and price changes on wage inequality, we construct the following measures for the 90/10, 90/50 and 50/10 log wage ratio in each country separately

$$\underbrace{\Delta\hat{q}_{90} - \Delta\hat{q}_{10}}_{\text{Overall}} = \underbrace{(\Delta\hat{q}_{X,90} - \Delta\hat{q}_{X,10})}_{\text{Composition}} + \underbrace{(\Delta\hat{q}_{S,90} - \Delta\hat{q}_{S,10})}_{\text{Wage Structure}} \tag{3.3}$$

$$\Delta\hat{q}_{90} - \Delta\hat{q}_{50} = (\Delta\hat{q}_{X,90} - \Delta\hat{q}_{X,50}) + (\Delta\hat{q}_{S,90} - \Delta\hat{q}_{S,50}) \tag{3.4}$$

$$\Delta\hat{q}_{50} - \Delta\hat{q}_{10} = (\Delta\hat{q}_{X,50} - \Delta\hat{q}_{X,10}) + (\Delta\hat{q}_{S,50} - \Delta\hat{q}_{S,10}) \tag{3.5}$$

The results of the Oaxaca-Blinder decompositions are shown in Table 2. In the three countries we observe a very similar pattern: changes in the skill and demographic composition of the workforce have had an unequalizing effect on the distribution of earnings as measured by the log 90/10 wage ratio. In Argentina, the counterfactual change is relatively small (5.7% increase), but it is sizeable in Chile (28.3% increase) and Brazil (32.6% increase).[13] These unequalizing effects of compositional changes are observed at both ends of the earnings distribution, but the magnitude tends to be larger in the upper half (90/50 wage ratio). In Brazil and Chile, composition changes would have pushed up the 90/50 wage ratio by 25 and 20 percent, respectively. Thus, changes in the skill-demographic composition alone cannot explain the observed patterns in earning inequality dynamics over the last two decades.

Wage structure effects are key to understanding the evolution of inequality. Earnings inequality would have declined by 13 percent had changes in the composition of the labor force been kept constant in Argentina, and as much as 41 percent in Chile and 67 percent in Brazil. Of course, these are partial equilibrium counterfactuals, which do not take into account the impact compositional changes may have had on the returns to observable characteris-

[13] All percent changes are calculated by taking the exponential of the respective values, which are expressed in logarithms, and subtracting one.

tics, an aspect to which we will address below.

Among the wage structure effects, changes in the schooling premiums had a prominent role in the observed inequality trends in the three countries, outweighing the observed inequality decline. Thus, changes in the schooling premium more than offset composition changes that were unequalizing during the period, and other unobservable factors that swam against the current of declining inequality. This is particularly remarkable in Brazil and Chile, where, under our counterfactual scenario, changes in the schooling premium would have contributed to a decline in the 90/10 interquartile range of 68 and 81 percent, respectively.

But education was not the only aspect of human capital that contributed to the fall of overall inequality during the 2000s. Changes in the experience premium also played a significant role. In Argentina, the contribution of the decline in the experience premium (24.6%) was as important as the contribution of the schooling premium. In Brazil and Chile the role of schooling was larger, but the importance of the decline in the experience premium is also remarkable. Although changes in the gender wage gap also had equalizing effects, their impact on overall inequality trends was much smaller.

Interestingly, inequality appears to be driven by different forces in the lower and upper half. The change in the schooling premium is the fundamental factor behind the evolution of the 50/10 interquartile range, but it is only significant in the evolution of inequality in the upper half of the distribution in Chile. In contrast, changes in the experience premium are fundamental to understanding upper-half inequality. In Argentina and Brazil, they alone almost fully explain changes in the 90/50 interquartile range almost fully. In Chile, their role with respect to changes in the schooling premium is more modest, but they are still a significant factor.

The decomposition exercise shows that the observed patterns in earnings inequality are mostly driven by how the wage structure changed over time, but it gives no indication as to why those relative returns changed. Moreover, the wage structure effects are calculated under a counterfactual in which the skill-demographic composition of the workforce is held constant, which we know was not the case. A natural hypothesis, then, is that the wage structure is changing because of the compositional changes, not in spite of them. This would be the case if workers with different skill-demographic characteristics are not perfectly substitutable in production, so that changes in relative supplies directly influence relative wages. In the next section we provide descriptive evidence that this simple mechanism is consistent with the observed trends and then proceed to formulate a model that can rationalize the patterns in the data.

4 Skill Supply and Demand and the Evolution of Relative Returns

The schooling premiums follow quite closely the evolution of earnings inequality. This is particularly the case with the high-school vs. primary wage gap, as evidenced by Figure 2, which shows the evolution of compositionally adjusted high school/primary and college/high school premiums in each country. The composition adjustment holds constant the relative employment shares of the different skill-demographic groups at their average levels across all years of the sample. In particular, we first compute mean (predicted) log real earnings in each country-year for 70 skill-demographic groups (five education levels, seven potential experience categories in five-year intervals, males and females). Mean wages for broader groups shown in the figures are then calculated as fixed-weighted averages of the relevant sub-group means, where the weights are equal to the mean employment share of each sub-group across all years. This adjustment ensures that the estimated premiums are not mechanically affected by compositional shifts.

The peaks in overall (90/10) inequality coincide with the peaks in the high-school vs. primary wage gap in Argentina and Chile, and they are both falling since the start of the sample in Brazil. The decline in high school/primary premiums is substantial. After the peak, the high school premium declined by 12 percent in Argentina, 19 percent in Chile, and 46 percent in Brazil. College vs. high-school premiums are also falling during the same period, although at a slower pace in Brazil and Chile. In Argentina, where the expansion of secondary took place earlier and employment of college graduates gains ground with respect to high school quickly (see Table 1), the reduction of the college premium is even larger than the one observed for the high-school vs. primary wage gap (22% since 2002).

Returns to experience declined across the board. Table 3 shows the change over time of the compositionally adjusted log hourly earnings of high experience (more than 20 years of potential experience) and low experience (less than 20 years) workers. Reductions of the experience premium were larger among high school and college graduates, the two education groups that are rapidly expanding in the three countries. The reduction of the experience premium is largest in Chile, where the employment share of workers with more than 20 years of potential experience grew faster (12 percentage points, as shown in Table 1). Thus, in the case of experience there also appears to be a connection between changes in relative supply and the evolution of returns.

Relative quantities and relative prices are moving in opposite directions for the two main drivers of the change in the wage structure: education and potential experience. To what extent can the trends in inequality be explained by this simple mechanism? The answer to this question will depend on the sensitivity of changes in relative wages to movements in relative supplies, that is, to the degree of substitutability between labor types with different skills. We now formalize this idea in a stylized model of supply and demand of skills. We then proceed to estimate the main parameters of the model using the data from the three countries.

4.1 A Supply-Demand Model

The basic framework follows the canonical work of Katz and Murphy (1992) and Murphy and Welch (1992) and Katz and Autor (1999). Workers are divided into skill groups, which are allowed to be imperfect substitutes in production. In particular, we assume that aggregate production in this economy can be described by a multilevel nested constant elasticity of substitution (CES) function. At the top level, output is produced as a CES combination of labor with high (college education completed or more) and low (high school degree at most) skills,

$$Y_t = \lambda_t \left(L_{Ut}^{\rho} + \alpha_t L_{St}^{\rho} \right)^{1/\rho}, \tag{4.1}$$

where Y_t is total output at time t; L_U is the total supply of low-skill labor; L_S is the total supply of high-skill labor; λ_t is a scale parameter that is allowed to vary in time to capture skill-neutral technological change; α_t is a time-varying parameter that captures both differences in relative productivities between skilled and unskilled labor, and movements in relative demands between this two types; and ρ is a function of the elasticity of substitution (σ_ρ) between skilled and unskilled labor: $\sigma_\rho = \frac{1}{1-\rho}$.

As noted by Katz and Autor (1999), the fact that we model the economy using an aggregate production function means that we have to be careful not to interpret the parameters as if we were dealing with individual firms. For example, the elasticity of substitution σ_ρ reflects not only technical substitution possibilities between workers at the firm level, but also outsourcing and substitution across goods and services in consumption. In a similar way, α_t captures relative productivity changes both at the intensive (workers performing better at the current jobs) and the extensive margins (e.g., a shift in work tasks across workers of different skill groups), changes in relative prices or quantities of non-labor inputs, and shifts in product demands among industries with different skill intensities.

Following Manacorda et al. (2010), we further divide the total supply of unskilled labor (L_{Ut}) into two sub-groups. The first sub-group is formed by labor from workers that have at least obtained a high school degree, but that have not completed any post-secondary education. The second sub-group comprises labor from workers that have at most obtained a primary education degree.[14] The aggregation is done using a productivity-weighted CES combination of the form

$$L_{Ut} = \left(L_{Pt}^{\delta} + \beta_t L_{Ht}^{\delta}\right)^{1/\delta}, \tag{4.2}$$

where L_{Pt} is the total supply of labor from workers with at most primary education; L_{Ht} is the total supply of labor from workers with at most secondary education; β_t is a time-varying parameter that captures both differences in relative productivities between the two sub-groups and changes in relative demands; and δ is a function of the elasticity of substitution (σ_δ) between the two low-skill types.

Finally, we divide workers in each of the three schooling categories (primary, high school and college educated) into two potential experience sub-groups. The first sub-group is composed of workers that have less than 20 years of potential experience, henceforth denominated as inexperienced workers. The second sub-group comprises workers with 20 years of potential experience or more, henceforth denominated as experienced workers. In practice, we aggregate experience and inexperience workers within schooling levels using a productivity-weighted CES combination. In order to reduce the parameter space, we assume that the elasticities of substitution and the relative productivity parameters within the unskilled group (primary and high school educated)

[14] Hence, high school dropouts are included in this group.

are the same. In particular, we have

$$L_{Kt} = \left(L_{KIt}^{\theta_U} + \phi_{Ut} L_{KEt}^{\theta_U}\right)^{1/\theta_U} \quad \text{for} \quad K = P, H \tag{4.3}$$

$$L_{St} = \left(L_{SIt}^{\theta_S} + \phi_{St} L_{SEt}^{\theta_S}\right)^{1/\theta_S}, \tag{4.4}$$

where I and E index inexperienced and experienced workers, respectively; ϕ_{Ut} and ϕ_{St} are time-varying parameters that capture both differences in relative productivities and changes in relative demands between the potential experience sub-groups; and θ_U and θ_S are both functions of the elasticities of substitution (σ_{θ_U} and σ_{θ_S}) between the two experience sub-groups within the skilled and unskilled labor types.[15]

We make two final assumptions that are key to our identification strategy. First, we assume that the labor supply of each labor type is exogenously determined. We acknowledge that this is a strong assumption, especially since we observe a sharp movement of women into the labor market during the last 20 years. Our choices for the relative wage and relative supply series discussed in the next section are made to ameliorate problems of selection arising from endogenous responses of women to changes in market conditions and endogenous responses of labor participation across different skill groups. The robustness section discusses alternative specifications to assess the sensitivity of the results.

Second, we assume that the economy is operating along the competitive equilibrium demand curve. The implication of these assumptions is that the wage of each labor type is fully determined by its marginal productivity. Given that we have six different labor types in the model (3 schooling levels $\times$ 2 potential experience groups), we get six equilibrium conditions. Denoting lower-case variables as the natural logarithms of the respective upper-case variables, the four equilibrium conditions for the low-skill types (PI, PE, HI and HE) are summarized in the following expression

[15] Even though modeling choices were made trying to mimic the observed data patterns, there is necessarily some degree of arbitrariness. In the robustness section we estimate an alternative specification to assess the importance of some of the modeling assumptions for the results.

$$w_{KJt} = \log \zeta_{KJt} + \frac{1}{\sigma_\rho}(y_t - l_{Ut}) + \frac{1}{\sigma_\delta}(l_{Ut} - l_{Kt}) + \frac{1}{\sigma_{\theta_U}}(l_{Kt} - l_{KJt}) \quad \text{for} \quad K = H, P \quad \text{and} \quad J = E, I \tag{4.5}$$

where $\zeta_{PIt} = 1$; $\zeta_{PEt} = \phi_{Ut}$; $\zeta_{HIt} = \beta_t$; and $\zeta_{HEt} = \beta_t \phi_{Ut}$. In a similar way, the two equilibrium conditions for the high-skill types (SI and SE) are

$$w_{SJt} = \log \zeta_{SJt} + \frac{1}{\sigma_\rho}(y_t - l_{St}) + \frac{1}{\sigma_{\theta_S}}(l_{St} - l_{SJt}) \quad \text{for} \quad J = E, I \tag{4.6}$$

where $\zeta_{SIt} = \alpha_t$; and $\zeta_{SEt} = \alpha_t \phi_{St}$.

The model has two types of relevant parameters that we wish to estimate: four parameters that are functions of the elasticities of substitution across types (ρ, δ, θ_U and θ_S), and a set of time varying relative productivities/demand shifters parameters (α_t, β_t, ϕ_{Ut} and ϕ_{St}). As shown by Johnson and Keane (2013), we could fit the trends in relative wages perfectly if we did not impose any restrictions on the evolution of the relative demand parameters, but this would mean that we would not be able to identify the parameters capturing the elasticities of substitution. We then restrict these relative productivities to follow a cubic trend in their natural logarithm.[16] For example, the parameter α_t is allowed to change according to

$$\log \alpha_t = \alpha_0 + \alpha_1 \times t + \alpha_2 \times t^2 + \alpha_3 \times t^3. \tag{4.7}$$

5 Results

5.1 Step I

The parameters of the model are estimated sequentially in three stages. In each stage we recover a subset of the parameters, and use them to construct the unobserved productivity weighted CES labor aggregates which are then used as inputs in the next step. For the first stage, we use the equilibrium

[16] We also tried quartic time trends without significant changes to our main results (results are available upon request). The estimated parameters associated with the fourth order of the quartic specification were no longer statistically significant. In the robustness section of the paper we also present the results from an exercise in which we allow for more flexibility in the specification of the time trends.

conditions from equations (4.5) to find the expression that characterizes the evolution of relative earnings between experienced and inexperienced labor within the unskilled labor types. In particular, we have

$$w_{KEt} - w_{KIt} = \phi_{Ut} - \frac{1}{\sigma_{\theta_U}}(l_{KEt} - l_{KIt}) \quad \text{for} \quad K = P, H. \tag{5.1}$$

The two equations in (5.1) show that changes in log relative wages between unskilled experienced labor and unskilled inexperienced labor depend on i) the evolution of the log relative supplies, scaled by the inverse of the elasticity of substitution; and ii) the evolution of relative demand (ϕ_{Ut}), which will be captured by a year-trend polynomial of order three. Note that the relative earnings and relative labor supply series can be constructed directly from the data in each country. In all cases we limit our sample to population between ages 16 and 65. The labor supply of each labor type is drawn from the entire working age population, irrespective of employment status or hours worked. Using working age population to construct labor supply is more appropriate in our context than using the employed population, considering the assumption that labor supply is exogenous in the model.[17]

The labor earnings series only uses full-time workers (reported working 35 hours or more) when estimating the average earnings of the labor types.[18] Moreover, we further restrict the sample to include only male workers when constructing the relative earnings series. This is done to address the concern of sample selection problems regarding female participation in the labor market, especially in a period of rapid movement of women into the workforce.

We estimate the two equations in (5.1) by OLS pooling the data from the three countries. We allow the demand trends to be country-specific but restrict the elasticities of substitutions to be common across countries. Both equations in (5.1) are estimated in a single regression that includes a skill dummy indicator (P/H). Results of the first step estimates are shown in column 1 of Table 4. High and low experience workers within the unskilled group are not perfect substitutes, with the point estimate of the elasticity of substitution around 3.2.[19] Based on the observed changes in relative supplies

[17]In the robustness section of the paper we show that using total employment or total hours worked has little effect on our estimates.

[18]We report the results when using both full-time and part-time workers in the robustness section of the paper.

[19]Using a different model specification for the United States, Card and Lemieux (2001) provide estimates of this elasticity between 4 and 6, while Johnson and Keane (2013) report

in each country, the estimated elasticity of substitution implies a predicted fall in the experience premium, absent any demand changes, of -6.6 percent in Argentina, -17 percent in Brazil, and -26 percent in Chile. This relative supply channel, by itself, closely matches the observed change in the experience premium within low-skilled types in Chile (-25.6%), but underestimates the observed fall in Argentina (-12.3%), and slightly overestimates the observed decline in Brazil (-12.6%). Figure 3 (Panel A) shows the negative co-movement of relative prices of experience and relative quantities, once the demand trends in Equation (5.1) are accounted for.[20]

We can also use the equilibrium conditions from Equations (4.6) to arrive at a similar expression for the evolution of relative earnings between experienced and inexperienced workers within the high-skilled types. This expression takes the form

$$w_{SEt} - w_{SIt} = \phi_{St} - \frac{1}{\sigma_{\theta_S}}(l_{SEt} - l_{SIt}). \tag{5.2}$$

We proceed symmetrically with the estimation of equation (5.2), as we did for the unskilled group. We cannot reject the null hypothesis that experienced and inexperienced workers are perfect substitutes within the high-skilled group, but the precision of the estimation is low, which can be partly explained by the small number of observations available for the regression (Table 4). Panel (b) of Figure (3) shows a scatter plot of log relative earnings and log relative supplies between experience groups among college-educated workers once the demand trends in equation (5.2) are accounted for. In contrast with the unskilled worker case, the regression line is virtually flat.

Figure 4 shows the evolution of the cubic demand trends captured by $\log \phi_{Ut}$ and $\log \phi_{St}$.[21] The results are heterogeneous across countries. In Argentina and Chile, relative demand for higher experience tended to increase during the 1990s, but has been either stagnant or in the decline since the beginning of the 2000s for both skilled and unskilled workers. The trend-reversal is also observed in Brazil, but the shift takes place later, by the middle of

estimates of around 10, which are not statistically significant.

[20] The log relative earnings series correspond to the residuals of a regression of the observed log relative earnings on country-specific cubic time trends and a skill dummy indicator. Correspondingly, the log relative supply series are obtained as the residuals of a regression of observed log relative supplies on country-specific cubic time trends and a skill dummy indicator.

[21] Each series is scaled so that it takes a value of zero at the first year in which data for the country is available.

the 2000s. Thus, the fall in the experience premiums where driven in part by ageing in the three countries. The supply effects were attenuated by a rise in relative demand for more experienced workers during the 1990s, and accentuated by a decline in relative demand during the 2000s.

5.2 Step II

The second step is aimed at recovering parameter estimates for the elasticity of substitution between the two low-skilled labor types (σ_δ), and for the time trends capturing the evolution of their relative demands ($\log \beta_t$). We use the equilibrium conditions from equations (4.5) to derive two equations characterizing the evolution of relative wages between workers with secondary education and those with at most primary education:

$$\begin{aligned} w_{HJt} - w_{PJt} = \beta_t - \frac{1}{\sigma_\delta}(l_{Ht} - l_{Pt})... \\ -\frac{1}{\sigma_{\theta_U}}\left[(l_{HJt} - l_{Ht}) - (l_{PJt} - l_{Pt})\right] \quad \text{for} \quad J = E, I, \end{aligned} \tag{5.3}$$

where both l_{Ht} and l_{Pt} are productivity-weighted CES labor aggregates. Although neither of the two labor aggregates is observed in the data, we can use the two equations in (4.3) and the estimated parameters from step I to calculate them. The second term in equation (5.3) is capturing overall (aggregated across experience groups) relative supplies between workers with at most primary education and workers with at most a high school degree. The last term represents relative changes in the potential experience composition between the two low skill groups. Note that the coefficient associated with this last term is the inverse elasticity of substitution between experience subgroups among unskilled workers, which was already estimated in step I. The estimated results in this second step serve as an internal consistency check.

We estimate both equations in (5.3) in a single regression, adding an experience group dummy indicator (E/I). As before, demand trends are allowed to be country-specific and approximated by a cubic trend, but the elasticities of substitution are assumed to be the same across countries. Results of the second step estimates are shown in column 3 of Table 4. The estimated elasticity of substitution between workers with at most primary education and workers with at most secondary education is 2.2. This number is in line with the 2.8 estimate found by Manacorda et al. (2010) for a different set of countries in the region during the 1990s, and reinforces the message that within the context of Latin America, there is a meaningful difference in the way the labor market treats the skills supplied by workers with secondary education and workers with at most primary completed. The estimate of σ_{θ_U} is very similar to that obtained in step I.

Panel (a) of Figure 5 shows the tight connection between changes in the high school premium vis-á-vis primary education and relative supply. The figure shows the evolution in the three countries of a log earnings and relative supply series that have been purged from country-specific demand trends and changes in the potential experience composition of the labor force. The negative co-movement between changes in labor supply and earnings is apparent, and confirmed by Panel (b) of Figure 5, which shows the estimated demand trends as captured by $\log \beta_t$. Relative demand for high school graduates was very stable in Brazil, increased weakly in Argentina, and only increased strongly in Chile during the 1990s. Thus, the observed sharp declines in the high school/primary schooling premiums were fundamentally driven by the educational upgrading of the workforce. Relative demand trends, if anything, favored high school graduates. This is further illustrated in Figure 6, which shows the fit of the model including or excluding demand trends. The exclusion of demand trends does not alter the model fit for Brazil, which is remarkably close to the observed relative wages. Over the whole period the decline of the high-school premium would have been larger in both Argentina and Chile had demand forces not favored high school graduates over those with basic education.

5.3 Step III

As a last step we obtain an estimate of the elasticity of substitution between skilled and unskilled labor (σ_ρ) to assess the role of relative skill labor supply on the observed changes in the skill premium. After some manipulation of Equations (4.5) and (4.6) we can derive the following four expressions,

$$\log\left(\frac{\widetilde{W_{SJt}}}{W_{KJt}}\right) = \log \alpha_t - \frac{1}{\sigma_\rho}\log\left(\frac{L_{St}}{L_{Ut}}\right) - \frac{1}{\sigma_\delta}\log\left(\frac{L_{Ut}}{L_{Kt}}\right) - \frac{1}{\sigma_{\theta_S}}\log\left(\frac{L_{SIt}}{L_{St}}\right) \ldots \\ - \frac{1}{\sigma_{\theta_U}}\log\left(\frac{L_{Kt}}{L_{KJt}}\right) \quad \text{for} \quad K = H, P \quad \text{and} \quad J = E, I, \tag{5.4}$$

where the terms $\log\left(\frac{\widetilde{W_{SJt}}}{W_{KJt}}\right)$ are the log relative earnings of skilled and unskilled workers of a given experience group that has been "demand-detrended" using the time trend estimates from the previous steps.[22] With the exception of L_{Ut} and L_{St}, all of the productivity-weighted CES labor aggregates have been previously used in the estimation. Constructing L_{Ut} and L_{St} is straightforward using the parameters previously estimated and equations (4.2) and (4.4).

The set of equations in (5.4) incorporate all the parameters of the production function. Hence, the estimation of these set of equations provides a third estimate for the elasticity of substitution σ_{θ_U}; a second estimate for both elasticities of substitution σ_{θ_S} and σ_δ; and a first estimate of the elasticity of substitution between skilled and unskilled workers σ_ρ. We estimate the four equations in a single regression, using a country-specific cubic demand trend for $\log\alpha_t$, and including skill-experience dummy variables as covariates.

Results of the third step estimates are shown in column 4 of Table 4. The estimated elasticity of substitution between skilled and unskilled labor is 2.1, very close to the elasticity of substitution between the two unskilled subgroups. Our point estimate for this elasticity is higher than the 1.4 and 1.6 values reported by Katz and Murphy (1992) and Johnson and Keane (2013) respectively for the United States; it is in line with the 2-2.5 range estimated by Card and Lemieux (2001) also in the United States; and is somewhat lower than the 2.5-5 range reported by Manacorda et al. (2010) for the Latin American region. Estimates of the other elasticities of substitution are very similar to those obtained in columns 1-3.

The results show that the large influx of college graduates into the labor market of the last 20 years depressed the college premium significantly. To see this more clearly, Panel (a) of Figure 7 shows a scatter plot of log relative earnings and log relative supplies once country-specific demand trends, changes in relative potential experience composition, and changes in schooling composition within the unskilled group are taken into account.[23] The negative

[22]In particular, $\log\left(\frac{\widetilde{W_{SEt}}}{W_{HEt}}\right) = \log\left(\frac{W_{SEt}}{W_{HEt}}\right) - \log\frac{\hat{\phi}_{st}}{\hat{\beta}_t\hat{\phi}_{Ut}}$; $\log\left(\frac{\widetilde{W_{SEt}}}{W_{PEt}}\right) = \log\left(\frac{W_{SEt}}{W_{PEt}}\right) - \log\frac{\hat{\phi}_{St}}{\hat{\phi}_{Ut}}$; $\log\left(\frac{\widetilde{W_{SIt}}}{W_{HIt}}\right) = \log\left(\frac{W_{SIt}}{W_{HIt}}\right) - \log\frac{1}{\hat{\beta}_t}$; and $\log\left(\frac{\widetilde{W_{SIt}}}{W_{PIt}}\right) = \log\left(\frac{W_{SIt}}{W_{PIt}}\right)$.

[23]The log earning series is constructed as the residuals of an estimation of Equation (5.4) that omits the aggregate relative supply term ($\log(L_{St}/L_{Ut})$). The log relative supply series corresponds to the residuals of an estimation of Equation (5.4) in which the aggregate relative

co-movement between relative supplies and relative earnings is evident. Panel (b) of Figure 7 shows the estimated relative demand trends between skilled and unskilled workers, as captured by $\log \alpha_t$ in Equation (5.4). In the three countries we observe a similar pattern, albeit with different magnitudes. Relative demand tended to favor college-educated workers during the 1990s, but this trend started to reverse around 2002. By the end of the period relative demand is back to the 1990s level in Argentina and Brazil, but remained higher in Chile.

Figure 8 shows the evolution of the observed skill premium and the predictions of the model in the three countries. The skill premium follows an inverted U-shaped pattern in Argentina and Chile, increasing up to the early 2000s and declining thereafter. This is very much in line with the observed evolution of inequality documented in Figure 1. Also in line with the evolution of inequality, the skill premium in Brazil declines slowly during the 1990s but more quickly during the 2000s.

Relative labor supply had a strong impact on the evolution of relative earnings by pulling the skill premium down. The dashed line in Figure 8 shows the predictions of the model where relative demand trends ($\log \alpha_t$) have been shut down. Labor supply changes alone actually over-predict the fall of the skill premium during the past two decades. However, they also completely miss the inverted U-shaped dynamics observed in Argentina and Chile, and in Brazil they strongly over-predict the inequality reduction. It is a strong demand for skills in the 1990s that slowly reverses in the 2000s that explains the inverted U shape of the skill premium. Thus, we conclude that while relative supply changes tended to pull the college premium downwards over the past 20 years, relative demand changes ameliorated this effect during the 1990s and magnified the relative supply channel after 2000.

5.4 The Role of the Minimum Wage, Unemployment and the Commodity Price Boom

The simple supply and demand framework presented above is silent about the role of institutional and cyclical conditions in the labor market in explaining changes in the wage structure. This is a limitation that may by relevant in our context because these economies have experienced sharp changes in labor market institutions such as the minimum wage and external conditions. The

supplies ($\log(L_{St}/L_{Ut})$) are used as the dependent variable.

commodity price boom that started in the early 2000s brought about sharp improvements in terms of trade and a period of unprecedented growth in the three countries (Erten and Ocampo, 2013; The World Bank, 2016). We follow Autor et al. (2008) and extend the empirical implementation of the model to examine the sensitivity of our estimates to including controls for changes in the minimum wage, unemployment, and terms of trade.

Figure 9 shows the evolution of minimum wages, unemployment and terms of trade in Argentina, Brazil and Chile over the period of analysis. Unemployment rose in the three countries during the late 1990s and early 2000s and then declined steadily after 2002 (Panel a). The pattern is particularly marked in Argentina, which suffered a major economic and financial crisis between the end of 2001 and 2003. The cyclical conditions in these economies, as captured by the unemployment rates, broadly coincide with the movements in the college premium previously documented. Between 1990 and 2012 the real hourly minimum wage increased by 120 percent in Brazil and by 138 percent in Chile. In Argentina it only increased after the 2001 crisis but at a fast pace, more than doubling in the decade that followed. Sharp increases in the minimum wage may result in substantial real wage gains for low-skilled workers, possibly contributing to the reduction of the skill premium. The commodity super cycle that started in 2002 (Panel c) benefited these three net commodity exporter countries, resulting in a rapid improvement in terms of trade (Panel d). The changes in relative skill demand at the start of the 2000s could be a result of a favorable product demand shift in the commodity sector, which tends to be intensive in low-skilled labor.

The extension of the empirical model is done by including the log of the real hourly minimum wage, the unemployment rate, and the log terms of trade index as covariates in the third step of the estimation of the model, which corresponds to Equation (5.4). We take advantage of the similar evolution across the three countries in the relative demand for skilled workers and restrict $\log \alpha_t$ to be common across countries. This allows us to simultaneously identify demand trends and the three additional covariates. To allow for greater flexibility in the evolution of demand we replace in this specification the third order polynomial time trend with a full set of year dummies.

Changing the specification of residual demand or including additional covariates does not alter the main message of previous sections: relative skill supply had an important role in the determination of the skill premium. Column I of Table 5 shows the baseline model estimates when we replace country-specific cubic time trends with a set of common year dummies. Results are very similar to our baseline mode except for a small reduction in the elasticity of substitution between skilled and unskilled workers, which declines from 2.1 to 1.5. If anything, relative supply trends become more important. Columns II-IV show the results when we include the three additional set of covariates one at a time and column V includes all the covariates in the same specification. The estimated elasticities of subsitution are very stable across specifications, and we cannot reject equality of the coefficients.

The estimated coefficients associated to the minimum wage have a negative sign and are statistically significant for Brazil and Chile in column V, with elasticities of -0.38 -0.50, respectively. Changes in the unemployment rate present different signs in Chile and Brazil. Improvements in the labor market appear to be associated with a decline (increase) of the college premium in Chile (Brazil). Terms of trade improvements during the 2000s appear to have contributed to the fall of the skill premium in Argentina and Brazil, while they are not significant in the case of Chile (Column V). This suggests that the commodity price boom of the last decade could be behind the shift in relative demand against skilled workers.

These alternative specifications provide some insights into what factors might be behind the residual demand trend reversal observed in the early 2000s. Panel (a) of Figure 10 shows the evolution of common demand trends as measured by the year specific fixed effects corresponding to Column I of Table 5. The trend reversal around the year 2002 in this baseline model is clearly depicted in the figure. In Panel (b) of Figure 10 we show the same demand trends for a model that includes controls for the log minimum wage and the unemployment rate. The inverted U-shaped pattern of residual demand is preserved, although the fall in relative demand for high-skill workers after 2002 is slightly attenuated.

A different story emerges when we include controls for the change in the terms of trade in each country (see Panel (c)). In this case we observe a deceleration of the relative demand for high-skill workers around 2002, but it is significantly smaller than the one estimated in the baseline model. Moreover, if we include the full set of controls the estimated relative skill demand remain flat after 2002. These results are suggestive that cyclical and institutional conditions of the labor market, especially regarding the improvements in external conditions of the economies following the commodity boom, were important determinants of the fall of the skill premium during the 2000s. In the absence of these changes, demand trends favoring high-skill workers would have attenuated the fall in earnings inequality brought about by the educational upgrading of the workforce.

6 Robustness

In this section we present a number of exercises aimed at understanding how sensitive our results are to modelling assumptions and sample decisions. Table 6 presents the last stage results of the model estimates using alternative supply measures. In our baseline specification (re-estimated in Column I) labor supply is calculated by adding up the total number of individuals of a given skill-demographic cell between the ages of 16 and 65. The second column of Table 6 presents the results when labor supply is approximated by the employed population in each cell. There are no significant changes in the estimated elasticities. In column 3 we present the same estimates when labor supply is calculated by adding up the total number of hours worked by each labor type. This is done to account for potential changes in the intensive margin. Since we only have information on hours worked for individuals that are employed, we impute those numbers for individual outside the workforce by assigning them the average number of hours worked by an employed worker with the same education, potential experience, and sex in the respective country-year. The elasticity of substitution between skilled and unskilled workers increases from 2.1 in our main specification to 2.6 when we use hours worked, but the rest of the parameters' point estimates are unchanged.

Table 7 replicates the results from Table 4, but including only workers aged 25-55. The sharp changes in the educational composition of the workforce might lead to sample selection issues associated with a larger share of younger workers remaining in the educational system, which would affect our wage series. Limiting the sample to prime age workers leads to slightly lower values of the different elasticities of substitution, so the relative supply channel is accentuated. All the relative demand trends have a pattern very similar to that presented in our preferred specification.

Table 8 presents the third stage results of an exercise in which we include both part-time and full-time workers in the calculation of the wage series. There is a small increase in the point estimate of the elasticity of substitution between high and low skilled workers when we use hours worked (2.7), but beyond this there are no major changes from our baseline results.

The particular structure we use when setting up the demand side of the model is based on the observed patterns in the data. But there is a degree of arbitrariness in modelling decisions, so that it is important to understand how sensitive our results are to alternative specifications. In Appendix A.4 we present a different formulation of the demand side that follows the work of Manacorda et al. (2010) with some modifications to allow for comparability to our estimates. There are two main differences with respect to our baseline model that are worth pointing out: first, the ordering of second and third levels of the production technology is reversed. In particular, skilled and unskilled workers are first disaggregated among seven experience groups, and then further divided between the two lowest schooling levels within each potential experience category. This change implies that the elasticity of substitution between potential experience groups is the same for skilled and unskilled workers by construction. Second, the number of potential experience groups is larger (seven in five-year intervals), but the identifying assumption is that the relative productivities/demand shifters between experience sub-groups is time-invariant. This is an important difference given that our baseline results show that relative demand for workers with higher experience levels has not remained constant.

The parameter estimates of this alternative model are presented in Table 9.[24] The elasticity of substitution between high school graduates and those who obtained at most a primary degree is larger than the 2.2 value estimated in our baseline result, with a magnitude that fluctuates between 2.68 and 3.78. These numbers are similar to those reported by Manacorda et al. (2010). Although not directly comparable, the point estimates in our model for the two elasticities of substitution between workers with different levels of potential experience ranged between 3 and 9, depending on the skill group. The analogous (single) estimate in the alternative specification is between 5.8 and 7.2. These new estimates are still statistically significant, but they imply that the sensitivity of relative wages to changes in relative supplies across experience groups is smaller in this set-up, more so among unskilled workers. Finally, in this alternative model the elasticity of substitution between skilled and unskilled workers falls, going from 2.1 to 1.3. This number is closer to similar elasticities estimated in the United States (see, Katz and Murphy (1992) and Johnson and Keane (2013)), and it would imply that the sensitivity of relative

[24]See Manacorda et al. (2010) for a description of the estimation procedure.

earnings to changes in relative supplies is even higher than what we found. The estimated demand trends are virtually unchanged.

7 Conclusions

After a decade of stagnant or rising earnings inequality, the distance between top and bottom earners in Latin America fell sharply during the late 1990s and 2000s. This trend was in sharp contrast to the experience of developed countries during the same period. This paper has offered a detailed accounting of the main factors behind the evolution of earnings inequality in three of the largest countries in the region: Argentina, Brazil and Chile.

The first suspect for changes in the wage structure is changes in the composition of the labor force. The three countries studied here were subject to similar employment changes, although in varying degrees: employees are aging and becoming more educated, and they are more likely to be females. We construct counterfactual wage distributions where the returns to labor market characteristics are kept fixed to evaluate how these changes in the composition of employment may have affected the distribution of wages. Our results are unambiguous. Changes in composition, particularly increased education, were inequality enhancing. Hence, while composition changes may have contributed to increasing wage inequality before the 2000s, they cannot explain the substantial decline of the last decade.

The decomposition also allows us to build counterfactual distributions where composition changes are kept constant to evaluate the role played by changes in the returns to labor market attributes. The analysis suggests a distinct role of education and experience premiums. The decline of the experience premium is key to explaining reductions of upper-tail (90/50 earnings gap) inequality. This is because reductions of the experience premium were stronger among the highly educated, perhaps reflecting some skill obsolescence. In contrast, a falling schooling premium bears a much higher weight in reducing inequality below the median (50/10 earnings ratio). This was driven by a much faster decline of the high school premium vis-à-vis workers who have at most completed primary education than the reduction of the college premium.

To link changes in schooling and experience premiums to the observed changes in labor supply we built a nested CES model where there is imperfect substitution across experience and education groups. A combination of a relative trend in demand that favored high school educated vis-à-vis primary educated workers during the 1990s, but slightly reversed during the 2000s, and a rapid educational upgrade go a long way toward explaining the high school/primary schooling premiums. A similar story can be told for the college premium. A rising supply of college educated workers has pushed the college premium downwards, but this is not enough to explain the reduction that started around 2000. We find instead that the demand for college-educated workers fell during the 2000s in the three countries. Changes in the experience premium have also responded to the evolution of relative supplies, suggesting imperfect substitutability. Our estimate of the elasticity of substitution between experienced and inexperienced workers is between 3.3 and 3.6 among unskilled labor, and close to 9, and only marginally significant, among skilled labor. However, as with college-educated workers, the changing experience profile of the labor force is not sufficient to explain the reduction of the returns that took place during the 2000s.

We show that expanding our empirical model to account for changes in the minimum wage, unemployment and terms of trade does not mitigate the role of labor supply. The simple supply-demand framework retains substantial explanatory power in the evolution of the wage premium. However, the sharp increases of the minimum wage in these countries, and more importantly improvements in terms of trade, go a long way toward identifying the residual change in the model. The decline in the demand for skills is associated with terms of trade improvements and the minimum wage. The results are also robust to using different measures of labor supply and to alternative specifications of the underlying theoretical model.

Our exposition focused on the common factors that have driven earnings inequality in the three countries, but in spite of commonalities, substantial heterogeneity remains. Brazil witnessed a much more pronounced reduction in earnings inequality than Argentina and Chile. Top and bottom inequality reductions took place in parallel in Brazil and Chile, while the decline of inequality in Argentina was fundamentally driven by the evolution in the upper half of the distribution. In Chile the demand for high-skilled workers increased much more rapidly during the 1990s than in Brazil and Argentina, and in spite of the recent fall remains above its 1990 level by 2013. The study shows how different relative skill supply trends, and differences in the evolution of minimum wages, unemployment and terms of trade can help explain some, but not all of these heterogeneous trends.

References

Acemoglu, D. and Autor, D. (2011). Skills, Tasks and Technologies: Implications for Employment and Earnings. In Ashenfelter, O. and Card, D. (eds), *Handbook of Labor Economics*. Elsevier, *vol. 4B*, chap. 12.

Adao, R. (2015). Worker Heterogeneity, Wage Inequality, and International Trade: Theory and Evidence from Brazil. Unpublished paper, MIT.

Autor, D., Katz, L. and Kearney, M. (2005). Rising wage inequality: The role of composition and prices. NBER Working Paper Series 11628.

Autor, D., Katz, L. and Kearney, M. (2008). Trends in U.S. inequality: Revising the revisionists. *The Review of Economics and Statistics* 90(2): pp. 300–323.

Azevedo, J. P., Inchauste, G. and Sanfelice, V. (2013). Decomposing the recent inequality decline in Latin America. Policy Research Working Paper Series 6715, The World Bank.

Battistón, D., García-Domench, C. and Gasparini, L. (2014). Could an Increase in Education Raise Income Inequality? Evidence for Latin America. *Latin American Journal of Economics-formerly Cuadernos de Economía* 51: 1–39.

Behrman, J., Birdsall, N. and Szekely, M. (2007). Economic Policy Changes and Wage Inequality in Latin America. *Economic Development and Cultural Change* 56(1): pp. 57–97.

Bourguignon, F., Ferreira, F. H. and Lustig, N. (2005a). *The Microeconomics of Income Distribution Dynamics in East Asia and Latin America*. No. 14844 in World Bank Publications. The World Bank.

Bourguignon, F., Ferreira, F. H. and Lustig, N. (2005b). *The Microeconomics of Income Distribution Dynamics in East Asia and Latin America*. No. 14844 in World Bank Publications. The World Bank.

Card, D. and Lemieux, T. (2001). Can falling supply explain the rising return to college for younger men? a cohort-based analysis. *The Quarterly Journal of Economics* 116(2): pp. 705–746.

Cavallo, A. (2013). Online and Official Price Indexes: Measuring Argentina's Inflation. *Journal of Monetary Economics* 60(2): pp. 152–165.

CEDLAS and The World Bank (2014). A Guide to SEDLAC: Socio-Economic Database for Latin America and the Caribbean.

Cornia, A. (2010). Income Distribution Under Latin America's New Left Regimes. *Journal of Human Development and Capabilities* 11(1): pp. 85–114.

Costa, F., Garred, J. and Pessoa, J. P. (2016). Winners and losers from a commodities-for-manufactures trade boom. *Journal of International Economics* 102: 50–69.

Cowell, F. and Victoria-Feser, M.-P. (1996). Robustness properties of inequality measures. *Econometrica* 64(1): pp. 77–101.

Cragg, M. I. and Epelbaum, M. (1996). Why has wage dispersion grown in Mexico? is it the incidence of reforms or the growing demand for skills? *Journal of Development Economics* 51(1): pp. 99–116.

Erten, B. and Ocampo, J. A. (2013). Super Cycles of Commodity Prices Since the Mid-Nineteenth Century. *World Development* 44: 14–30.

Essama-Nssah, B. and Lambert, P. (2011). Influence functions for distributional statistics. ECINE Working Paper 236.

Ferreira, F., Leite, P. and Litchfield, J. (2008). The Rise and Fall of Brazilian Inequality. *Macroeconomic Dynamics* 12(2): pp. 199–230.

Firpo, S., Fortin, N. and Lemieux, T. (2007). Decomposing wage distributions using recentered influence functions. Unpublished manuscript, PUC-Rio and UBC.

Firpo, S., Fortin, N. and Lemieux, T. (2009). Unconditional Quantile Regressions. *Econometrica* 77(3): pp. 953–973.

Galiani, S. and Sanguinetti, P. (2003). The impact of trade liberalization on wage inequality: Evidence from argentina. *Journal of Development Economics* 72(2003).

Gasparini, L., Cruces, G. and Tornarolli, L. (2011). Recent Trends in Income Inequality in Latin America. *Economia* 11(2): pp. 147–201.

Gasparini, L. and Lustig, N. (2011). The Rise and Fall of Income Inequality in Latin America. In Ocampo, J. A. and Ros, J. (eds), *The Oxford Handbook of Latin American Economics*. Oxford University Press.

Goldberg, P. K. and Pavcnik, N. (2007). Distributional Effects of Globalization in Developing Countries. *Journal of Economic Literature* 45: 39–82.

Green, F., Dickerson, A. and Saba Arbache, J. (2001). A Picture of Wage Inequality and the Allocation of Labor Through a Period of Trade Liberalization: The Case of Brazil. *World Development* 29: 1923–1939.

Halliday, T., Lederman, D. and Robertson, R. (2015). Tracking wage inequality trends with prices and different trade models : evidence from Mexico. Policy Research Working Paper Series 7471, The World Bank.

Johnson, M. and Keane, M. (2013). A Dynamic Equilibrium Model of the US Wage Structure, 1969-1996. *Journal of Labour Economics* 31(1): pp. 1–49.

Kahhat, J. (2010). Labor earnings inequality: The demand for and supply of skills. In López-Calva, L. F. and Lustig, N. (eds), *Declining Inequality in Latin America: A Decade of Progress?*. Brookings Institution Press, chap. 2.

Katz, L. and Autor, D. (1999). Changes in the wage structure and earnings inequality. In Ashenfelter, O. and Card, D. (eds), *Handbook of Labor Economics*. Amsterdam: North-Holland, *vol. 3A*, chap. 26.

Katz, L. and Murphy, K. (1992). Changes in relative wages, 1963-1987: Supply and demand factors. *The Quarterly Journal of Economics* 107(1): pp. 35–78.

Lemieux, T. (2006). Increasing Wage Inequality: Composition Effects, Noisy Data, or Rising Demand for Skill? *The American Economic Review* 96(3): pp. 461–498.

Lemieux, T., MacLeod, B. and Parent, D. (2009). Performance Pay and Wage Inequality. *Quarterly Journal of Economics* 124(1): pp. 1–49.

Levy, S. and Schady, N. (2013). Latin america's social policy challenge: Education, social insurance, redistribution. *Journal of Economic Perspectives* 27: 193–218.

Londoño, J. L. and Szekely, M. (2000). Persistent Poverty and Excess Inequality: Latin America, 1970-1995. *Journal of Applied Economics* 3(1): pp. 93–134.

Lopez-Calva, L. F. and Lustig, N. (2010). *Declining Inequality in Latin America: A Decade of Progress?*. Brookings Institution Press.

López-Calva, L. F. and Lustig, N. (2010). Explaining the decline in inequality in Latin America: Technological change, educational upgrading, and democracy. In López-Calva, L. F. and Lustig, N. (eds), *Declining Inequality in Latin America: A Decade of Progress?*. Brookings Institution Press, chap. 1.

Lustig, N., Lopez-Calva, L. and Ortiz-Juarez, E. (2013). Deconstructing the Decline in Inequality in Latin America. Tulane Economic Working Paper Series.

Manacorda, M., Sánchez-Paramo, C. and Schady, N. (2010). Changes in Returns to Education in Latin America: The Role of Demand and Supply of Skills. *Industrial and Labor Relations Review* 63(2): pp. 307–326.

Messina, J. and Silva, J. (2016). Wage Inequality in Latin America. Understanding the Past to Prepare the Future. World Bank Unpublished Manuscript.

Murphy, K. and Welch, F. (1992). The Structure of Wages. *The Quarterly Journal of Economis* 107(1): pp. 285–326.

Murphy, K. M. and Welch, F. (1990). Empirical Age-Earnings Profiles. *Journal of Labor Economics* 8: 202–229.

Pavcnik, N. (2003). What explains skill upgrading in less developed countries? *Journal of Development Economics* 71: 311 – 328.

Robertson, R. (2004). Relative prices and wage inequality: evidence from mexico. *Journal of International Economics* 64: 387 – 409.

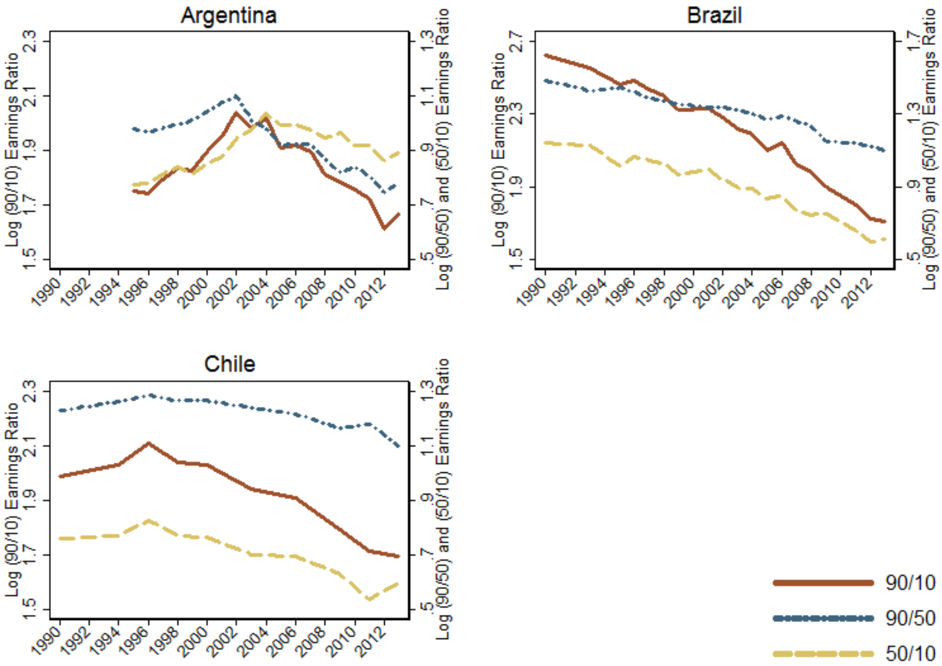
Sanchez-Paramo, C. and Schady, N. (2003). Off and Running? Technology, Trade, and the Rising Demand for Skilled Workers in Latin America. The World Bank. Policy Research Working Paper 3015.

The World Bank (2016). The Commodity Cycle in Latin America: Mirages and Dilemas. Semiannual Report, Office of the Regional Chief Economist.

A Appendix

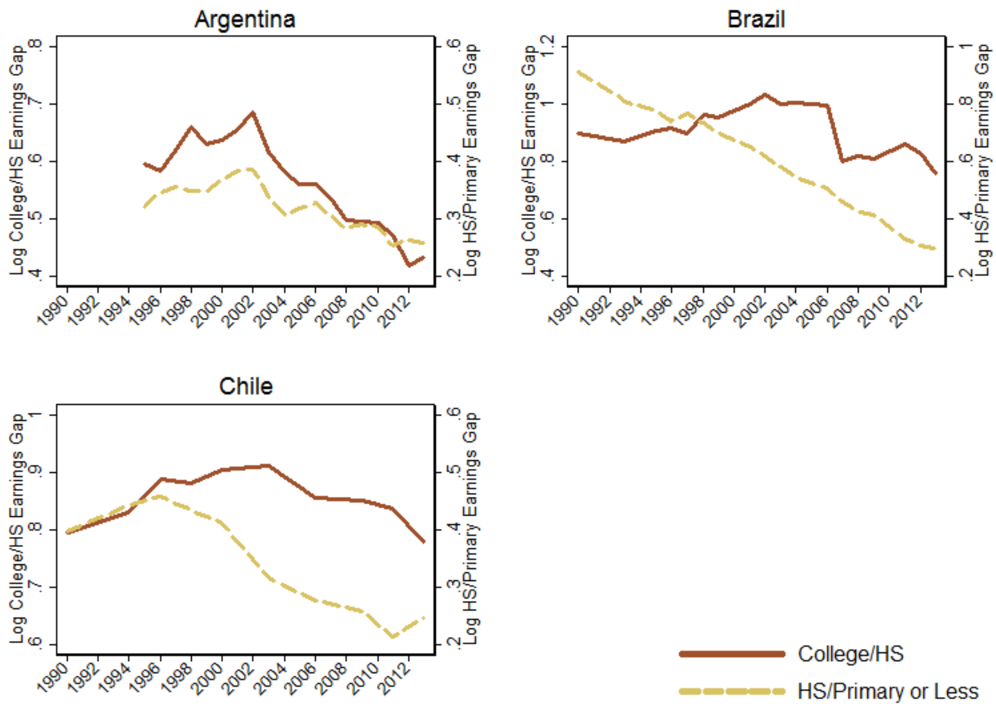
A.1 Tables and Figures

Figure 1: Interquantile Log Earnings Ratio by Country



Notes: Sample consists of full-time workers (reported working 35 hours or more) between ages 16 and 65.

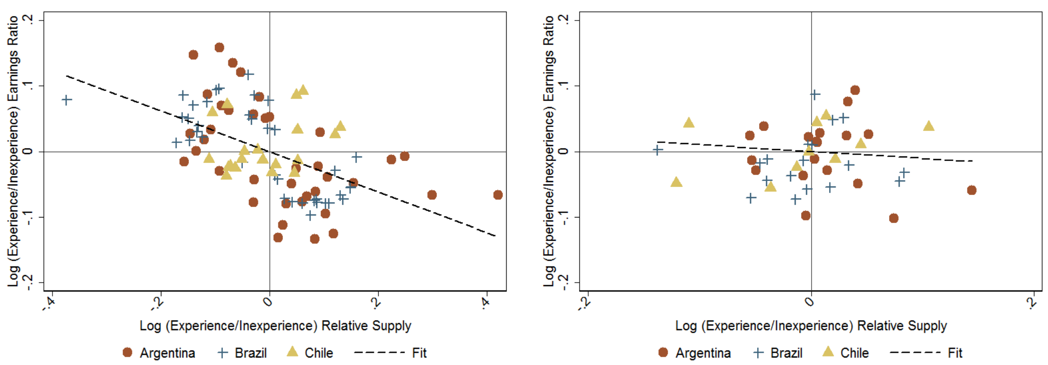
Figure 2: Composition-Adjusted College/High School and High School/Primary Earnings Gap



Notes: Sample consists of full-time workers (reported working 35 hours or more) between ages 16 and 65. See Appendix A for details on the construction of the compositionally adjusted series.

Figure 3: Adjusted Relative Earnings and Relative Supplies by Experience Level

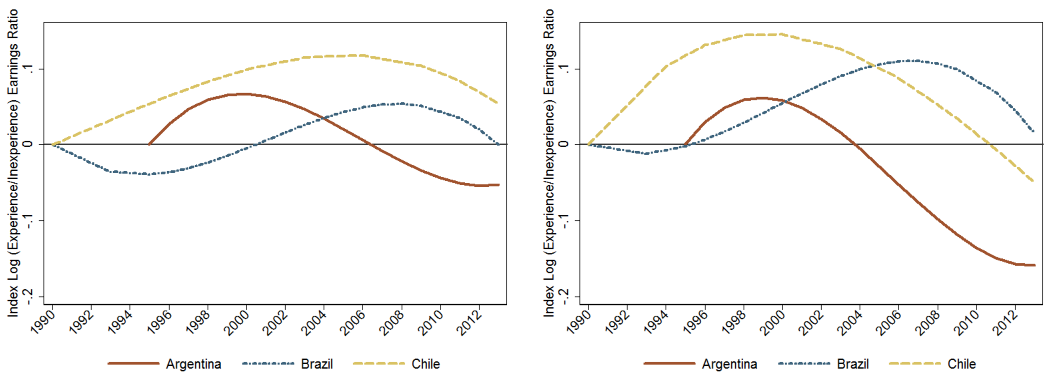
(a) Unskilled Workers (b) Skilled Workers



Notes: Log relative earnings correspond to the residuals from a regression of observed relative earnings on country-specific cubic time trends and a skill dummy. Log relative supplies correspond to the residuals from a regression of observed relative supplies on country-specific cubic time trends and a skill dummy.

Figure 4: Experienced/Inexperienced Demand Index by Skill Level

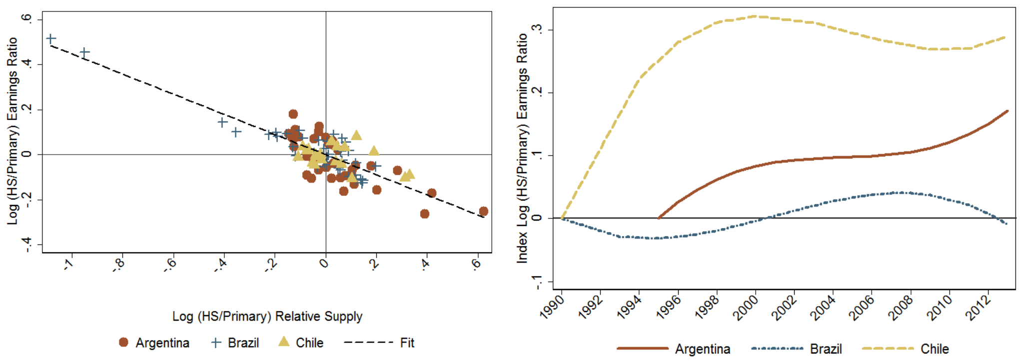
(a) Unskilled Workers ($\log \hat{\phi}_{Ut}$) (b) Skilled Workers ($\log \hat{\phi}_{St}$)



Notes: Relative demand trends between experienced and inexperienced workers are country-specific cubic time trends estimated following Equations (5.1) and (5.2). Each series is scaled so that it takes a value of zero at the first year in which data for the country are available.

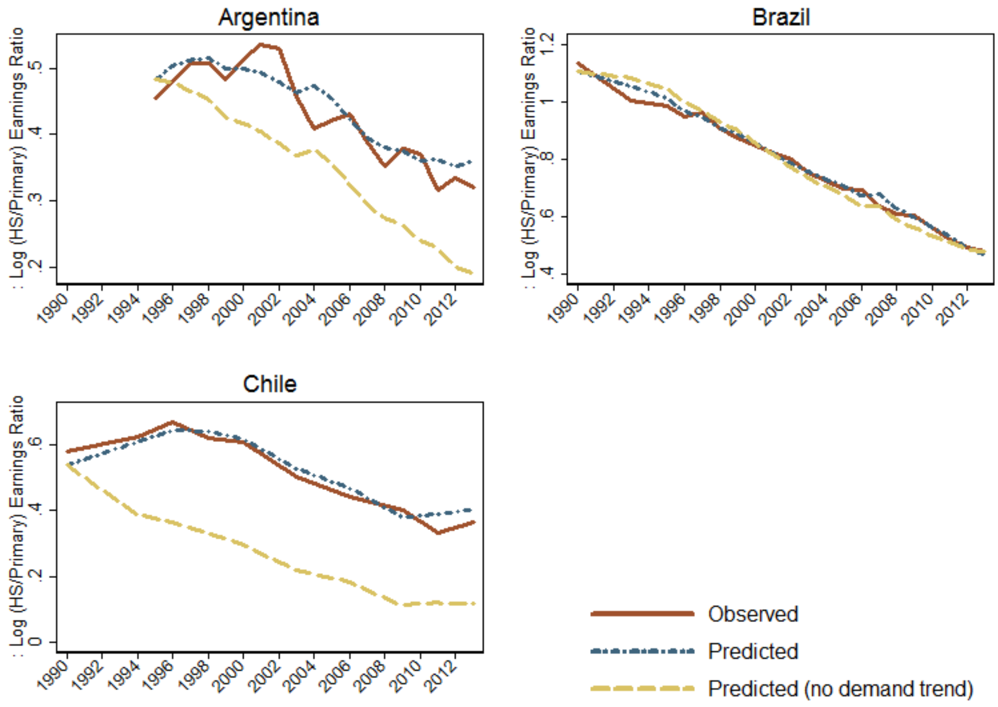
Figure 5: Supply and Demand Factors Behind the Fall in the High-School/Primary Earnings Gap

(a) Relative Earnings and Supplies (b) HS/Primary Demand Index ($\log \hat{\beta}_t$)



Notes: Panel A depicts log relative earnings and log relative supplies of workers with at most a high school degree with respect to those with only primary education, once the country-specific demand trends and changes in the relative potential experience composition are taken into account. The log earning series is constructed as the residuals of an estimation of Equation (5.3) that omits the aggregate relative supply term ($l_{Ht} - l_{Pt}$). The log relative supply series corresponds to the residuals of an estimation of Equation (5.3) in which the aggregate relative supplies ($l_{Ht} - l_{Pt}$) are used as the dependent variable. Panel (b) depicts the estimated relative demand trends between workers with at most a high school degree and those with only primary schooling as captured by the country-specific cubic time trends in Equation (5.3). Each series is scaled so that it takes a value of zero at the first year in which data for the country are available.

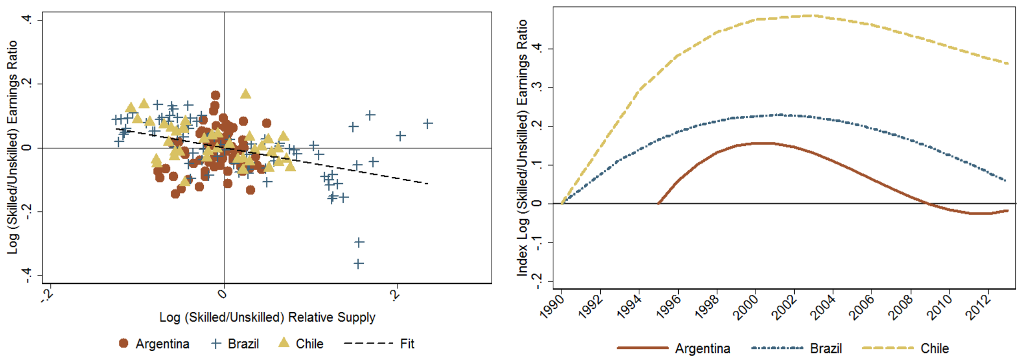
Figure 6: High School/Primary Observed and Predicted Relative Earnings



Notes: "Observed" refers to the Log (HS/Primary) Earnings Ratio observed in the data. "Predicted" refers to the model prediction derived from the estimation of Equation (5.3). "Predicted (no demand trend)" is the prediction of a modified version the model in Equation (5.3) that omits the country-specific time trends.

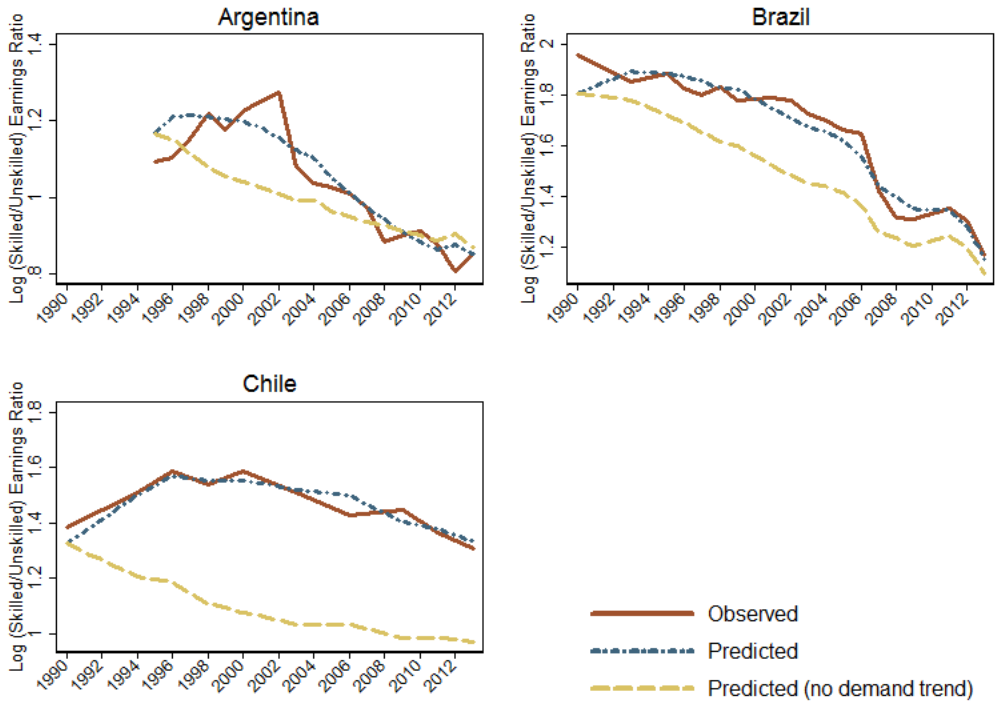
Figure 7: Supply and Demand Factors Behind the Fall in the Skilled/Unskilled Earnings Gap

(a) Relative Earnings and Supplies (b) Skilled/Unskilled Demand Index ($\log \hat{\alpha}_t$)



Notes: Panel A depicts log relative earnings and log relative supplies of skilled with respect to unskilled workers once the country-specific demand trends, changes in relative potential experience composition, and changes in schooling composition within the unskilled group are taken into account. The log earning series is constructed as the residuals of an estimation of Equation (5.4) that omits the aggregate relative supply term ($l_{St} - l_{Ut}$). The log relative supply series corresponds to the residuals of an estimation of Equation (5.4) in which the aggregate relative supplies ($l_{St} - l_{Ut}$) are used as the dependent variable. Panel (b) depicts the estimated relative demand trends between skilled and unskilled workers as captured by the country-specific cubic time trend in Equation (5.4). Each series is scaled so that it takes a value of zero at the first year in which data for the country are available.

Figure 8: High School/Primary Observed and Predicted Relative Earnings

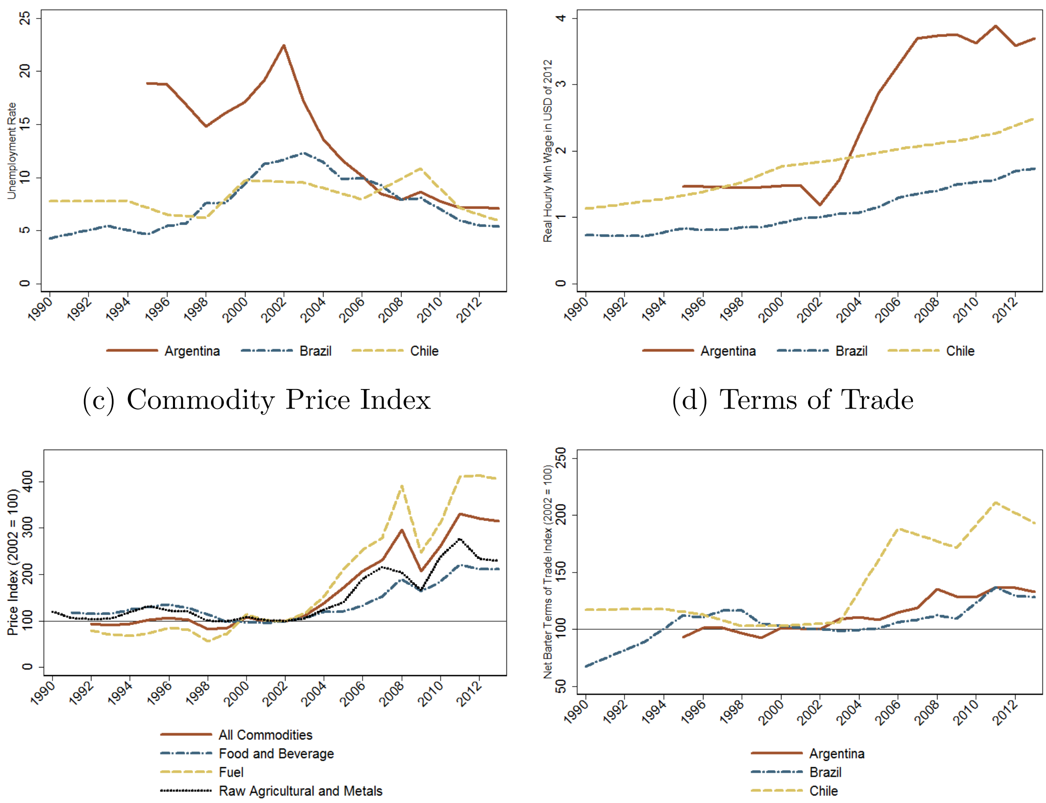


Notes: "Observed" refers to the Log (Skilled/Unskilled) Earnings Ratio observed in the data. "Predicted" refers to the model prediction derived from the estimation of Equation (5.4). The observed and predicted unskilled earnings series is constructed as a weighted average between the two low-skill sub-groups, where the weights correspond to the respective labor share. "Predicted (no demand trend)" is the prediction of a modified version the model in Equation (5.4) that omits the country-specific time trends.

Figure 9: Relative Skill Demand. Conditioning Factors

(a) Unemployment Rate (b) Minimum Wage

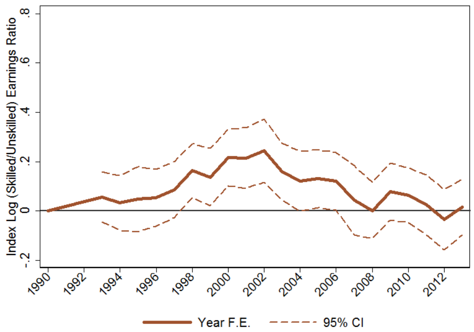
(c) Commodity Price Index (d) Terms of Trade



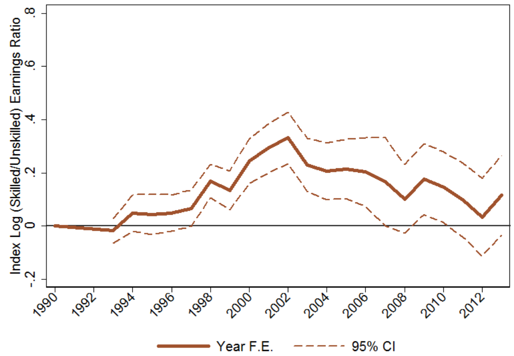
Notes: The unemployment rate series in Panel (a) is taken from the World Economic Outlook (WEO) database. The Minimum wage series in Panel (b) is taken from the annual indicators of the International Labour Organization (ILO). The source of the series in Panel (c) is The IMF's Primary Commodity Price System. The Food and Beverage series includes cereal, vegetable oils, meat, seafood, sugar, bananas, oranges, coffee, tea, and cocoa. The Fuel series includes crude oil (petroleum), natural gas, and coal. The Raw Agricultural and Metals series includes timber, cotton, wool, rubber, hides, copper, aluminum, iron ore, tin, nickel, zinc, lead, and uranium. See `http://www.imf.org/external/np/res/commod/index.aspx` for a description of the construction of the indices. The series in Panel (d) are taken from the United Nations Conference on Trade and Development (UNCTAD). Unit value indexes are based on data reported by countries, supplemented by UNCTAD's estimates using the previous year's trade values at the Standard International Trade Classification three-digit level as weights.

Figure 10: Skilled/Unskilled Demand Index. The Role of Unemployment, Minimum Wages and Commodity Prices

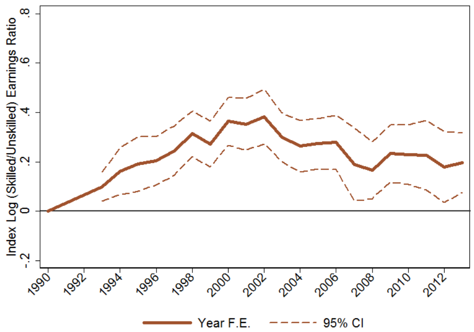
(a) Skilled/Unskilled Demand. Baseline



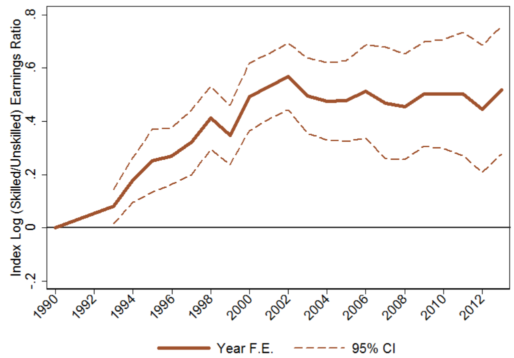
(b) Skilled/Unskilled Demand After Controlling for Minimum Wage and Unemployment Rate



(c) Skilled/Unskilled Demand After Controlling for Terms of Trade



(d) Skilled/Unskilled Demand After Controlling for Minimum Wage, Unemployment Rate and Terms of Trade



Notes: Each panel depicts the estimated relative demand trends between skilled and unskilled workers ($\log \hat{\alpha}_t$) using different specifications of the last stage of the baseline model. Panel (a) corresponds to the estimates of the year fixed effects of column I in Table 5. Panel (b) corresponds to the estimates of the year fixed effects of a model that includes controls for the unemployment rate and the natural logarithm of the minimum wage. Panel (c) corresponds to the estimates of the year fixed effects of column IV in Table 5, which includes controls for the log of the terms of trade index. Panel (d) corresponds to the estimates of the year fixed effects of column V in Table 5, which includes controls for the log real minimum wage, the unemployment rate of each country, and the log of the terms of trade index. The demand trends are scaled so that they take a value of zero in 1990.

Table 1: 100 $\times$ Change in Employment Share

	Argentina	Brazil	Chile
	1995-2013	1990-2013	1990-2013
Education			
Primary or less	-17.71	-34.53	-24.17
High School	7.70	22.42	10.79
College	10.02	12.11	13.38
Pot. Exper.			
[≥20]	-0.22	2.01	11.93
Sex			
Female	2.32	8.88	8.26
Educ. + Pot. Exper.			
Primary or less [0-19]	-8.16	-20.60	-15.57
Primary or less ≥ 20	-9.55	-13.93	-8.60
High School [0-19]	3.37	12.24	-3.00
High School ≥ 20	4.33	10.18	13.79
College [0-19]	5.01	6.35	6.64
College ≥ 20	5.01	5.76	6.74

Notes: Sample consists of full-time workers (reported working 35 hours or more) between ages 16 and 65. Tabulated numbers are changes in the employment shares for each group.

Table 2: Compositional Changes and Inequality Patterns: Oaxaca-Blinder Decomposition Results

	Argentina (1995-2013)		Brazil (1990-2013)		Chile (1990-2013)	
	Est.	[S.E]	Est.	[S.E]	Est.	[S.E]
Log (90/10)						
Overall	-0.091	[0.016]	-0.850	[0.017]	-0.290	[0.021]
Composition	0.056	[0.007]	0.282	[0.016]	0.249	[0.011]
Education	0.054	[0.007]	0.302	[0.016]	0.211	[0.010]
Experience	0.001	[0.001]	-0.003	[0.001]	0.051	[0.002]
Sex	0.002	[0.001]	-0.017	[0.001]	-0.013	[0.001]
Wage Structure	-0.147	[0.018]	-1.132	[0.028]	-0.538	[0.023]
Education	-0.271	[0.113]	-1.153	[0.121]	-1.685	[0.086]
Experience	-0.282	[0.044]	-0.825	[0.095]	-0.497	[0.055]
Sex	-0.049	[0.009]	-0.042	[0.008]	-0.033	[0.007]
Constant	0.454	[0.139]	0.888	[0.230]	1.677	[0.120]
Log (90/50)						
Overall	-0.214	[0.014]	-0.350	[0.011]	-0.149	[0.018]
Composition	0.056	[0.005]	0.222	[0.008]	0.183	[0.009]
Education	0.056	[0.005]	0.229	[0.009]	0.169	[0.009]
Experience	0.001	[0.001]	-0.001	[0.001]	0.030	[0.002]
Sex	-0.001	[0.000]	-0.005	[0.001]	-0.015	[0.001]
Wage Structure	-0.270	[0.015]	-0.572	[0.015]	-0.332	[0.021]
Education	0.084	[0.059]	0.076	[0.041]	-1.021	[0.072]
Experience	-0.253	[0.036]	-0.204	[0.054]	-0.297	[0.053]
Sex	-0.020	[0.005]	-0.013	[0.004]	-0.019	[0.007]
Constant	-0.080	[0.079]	-0.431	[0.090]	1.004	[0.102]
Log (50/10)						
Overall	0.123	[0.018]	-0.500	[0.013]	-0.140	[0.017]
Composition	0.001	[0.005]	0.060	[0.013]	0.065	[0.006]
Education	-0.002	[0.004]	0.073	[0.014]	0.042	[0.006]
Experience	-0.000	[0.001]	-0.002	[0.001]	0.021	[0.001]
Sex	0.003	[0.001]	-0.011	[0.001]	0.002	[0.001]
Wage Structure	0.123	[0.018]	-0.559	[0.024]	-0.206	[0.019]
Education	-0.355	[0.101]	-1.228	[0.095]	-0.664	[0.067]
Experience	-0.029	[0.039]	-0.621	[0.052]	-0.201	[0.027]
Sex	-0.028	[0.008]	-0.029	[0.006]	-0.014	[0.006]
Constant	0.534	[0.124]	1.319	[0.166]	0.672	[0.085]

Notes: Sample consists of full time workers (reported working 35 hours or more) between ages 16 and 65. Standard errors calculated via bootstrap with 100 replications.

Table 3: 100 × Changes in Real Composition-Adjusted Log Hourly Earnings

	Argentina 1995-2013	Brazil 1990-2013	Chile 1990-2013
All	12.23	0.58	37.58
Sex			
Male	12.38	-2.38	33.48
Female	11.87	6.33	45.69
Education			
Primary or less	20.09	28.94	48.83
High School	13.81	-32.71	33.76
College	-2.47	-46.76	32.09
Educ. + Pot. Exper.			
Primary or less [0-19]	21.40	35.55	62.18
Primary or less ≥ 20	19.82	25.61	43.30
High School [0-19]	21.03	-24.02	47.94
High School ≥ 20	4.39	-49.48	16.21
College [0-19]	3.82	-41.01	37.53
College ≥ 20	-13.33	-55.00	22.68

Notes: Sample consists of full time workers (reported working 35 hours or more) between ages 16 and 65. See Appendix A for details on the construction of the compositionally adjusted series.

Table 4: Model Estimation Results

	STEP			
	IA	IB	II	III
Elasticities				
$-1/\sigma_{\theta_U}$	-0.309***		-0.323***	-0.359***
	(0.047)		(0.059)	(0.039)
$-1/\sigma_{\theta_S}$		-0.104		-0.111
		(0.191)		(0.081)
$-1/\sigma_{\delta}$			-0.448***	-0.471***
			(0.022)	(0.018)
$-1/\sigma_{\rho}$				-0.478***
				(0.125)
Demand Argentina				
Time	0.031**	0.034	0.029*	0.067***
	(0.015)	(0.025)	(0.016)	(0.014)
Time^2/100	-0.417*	-0.538*	-0.290	-0.830***
	(0.230)	(0.276)	(0.243)	(0.171)
Time^3/1000	0.127	0.165*	0.102	0.253***
	(0.096)	(0.094)	(0.100)	(0.061)
Demand Brazil				
Time	-0.019**	-0.011	-0.016*	0.045**
	(0.008)	(0.017)	(0.009)	(0.016)
Time^2/100	0.265**	0.246	0.218**	-0.251
	(0.082)	(0.216)	(0.096)	(0.178)
Time^3/1000	-0.079***	-0.086	-0.066**	0.029
	(0.023)	(0.069)	(0.026)	(0.051)
Demand Chile				
Time	0.011	0.035**	0.076***	0.094***
	(0.011)	(0.013)	(0.013)	(0.017)
Time^2/100	0.016	-0.234	-0.562***	-0.557***
	(0.146)	(0.174)	(0.157)	(0.154)
Time^3/1000	-0.022	0.032	0.124**	0.094**
	(0.045)	(0.053)	(0.048)	(0.041)
N	96	48	96	192
R^2	0.801	0.660	0.943	0.959

*** 1 percent ** 5 percent * 10 percent. Robust standard errors in parenthesis.
Notes: Each column presents the results of the estimation of the different stages of the model. Column IA shows the OLS estimates of the inverse of the elasticity of substitution between experienced and inexperienced workers within the unskilled group ($\sigma_{\theta U}$) (see Equation (5.1)); column IB correspond to the OLS estimates of the inverse of the elasticity of substitution between experience and inexperience workers within the skilled group ($\sigma_{\theta S}$) (see Equation (5.2)); column II shows the OLS estimates of the inverse of the elasticity of substitution between the two unskilled sub-groups (σ_{δ}), and a second estimate of the inverse of the elasticity of substitution $\sigma_{\theta U}$ (see Equation (5.3)); finally, column III shows the OLS estimates of the inverse of the elasticity of substitution between skilled and unskilled labor (σ_{ρ}), as well as additional estimates from the other elasticities in the model.

Table 5: Model Estimation Results Skilled/Unskilled Premium: Including and Excluding the Minimum Wage, the Unemployment Rate, and the Terms of Trade Index.

	Common Year Fixed Effects				
	I	II	III	IV	V
Elasticities					
$-1/\sigma_{\theta_U}$	-0.272***	-0.290***	-0.287***	-0.283***	-0.301***
	(0.038)	(0.037)	(0.037)	(0.037)	(0.034)
$-1/\sigma_{\theta_S}$	-0.017	-0.102	-0.068	-0.060	-0.091*
	(0.077)	(0.070)	(0.054)	(0.059)	(0.048)
$-1/\sigma_{\delta}$	-0.446***	-0.442***	-0.448***	-0.446***	-0.448***
	(0.017)	(0.014)	(0.014)	(0.014)	(0.012)
$-1/\sigma_{\rho}$	-0.665***	-0.674***	-0.929***	-0.485***	-0.777***
	(0.085)	(0.079)	(0.089)	(0.082)	(0.111)
Log Real Min. Wage					
Argentina		-0.030			-0.083
		(0.050)			(0.126)
Brazil		-0.189**			-0.380**
		(0.086)			(0.121)
Chile		0.064			-0.507**
		(0.127)			(0.166)
Unemployment Rate					
Argentina			-0.009**		-0.008
			(0.003)		(0.008)
Brazil			-0.025***		-0.027***
			(0.005)		(0.006)
Chile			0.006		0.016*
			(0.009)		(0.008)
Log Terms of Trade					
Argentina				-0.109	-0.592**
				(0.109)	(0.239)
Brazil				-0.405***	-0.472***
				(0.089)	(0.102)
Chile				-0.007	-0.010
				(0.048)	(0.121)
N	192	192	192	192	192
R2	0.967	0.972	0.973	0.971	0.978
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Country Fixed Effects	Yes	Yes	Yes	Yes	Yes

*** 1 percent ** 5 percent * 10 percent. Robust standard errors in parenthesis.
Notes: The Table reports the third stage estimates of the parameters of the model when we include the natural logarithm of the real minimum hourly wage, the unemployment rate, and the natural logarithm of the terms of trade index. We include year and country fixed effects to capture relative demand trends.

Table 6: Model Estimation Results: Alternative Supply Measures

	Supply Measure		
	Working Age Pop.	Occupied Pop.	Total Hours Worked
Elasticities			
$-1/\sigma_{\theta_U}$	-0.359***	-0.337***	-0.321***
	(0.039)	(0.040)	(0.040)
$-1/\sigma_{\theta_S}$	-0.111	-0.128	-0.092
	(0.081)	(0.078)	(0.075)
$-1/\sigma_{\delta}$	-0.471***	-0.457***	-0.451***
	(0.018)	(0.018)	(0.018)
$-1/\sigma_{\rho}$	-0.478***	-0.505***	-0.393***
	(0.125)	(0.115)	(0.105)
Demand Argentina			
Time	0.067***	0.076***	0.075***
	(0.014)	(0.014)	(0.015)
Time^2/100	-0.830***	-0.958***	-0.920***
	(0.171)	(0.170)	(0.175)
Time^3/1000	0.253***	0.290***	0.274***
	(0.061)	(0.060)	(0.061)
Demand Brazil			
Time	0.045**	0.048**	0.055**
	(0.016)	(0.016)	(0.017)
Time^2/100	-0.251	-0.280	-0.289
	(0.178)	(0.171)	(0.178)
Time^3/1000	0.029	0.035	0.031
	(0.051)	(0.049)	(0.050)
Demand Chile			
Time	0.094***	0.088***	0.102***
	(0.017)	(0.015)	(0.015)
Time^2/100	-0.557***	-0.559***	-0.596***
	(0.154)	(0.139)	(0.143)
Time^3/1000	0.094**	0.105**	0.101**
	(0.041)	(0.038)	(0.039)
N	192	192	192
R^2	0.959	0.959	0.957

*** 1 percent ** 5 percent * 10 percent. Robust standard errors in parenthesis.
Notes: Each column presents the results of the estimation of the third stage of the model using alternative measures to construct total labor supply. The first column corresponds to our baseline results; the second column limits the sample to include only occupied population; and the final column uses total hours worked.

Table 7: Model Estimation Results. Prime Age Workers (25-55)

	STEP			
	IA	IB	II	III
Elasticities				
$-1/\sigma_{\theta_U}$	-0.345***		-0.398***	-0.426***
	(0.049)		(0.042)	(0.044)
$-1/\sigma_{\theta_S}$		-0.182		-0.195**
		(0.148)		(0.068)
$-1/\sigma_{\delta}$			-0.439***	-0.462***
			(0.023)	(0.019)
$-1/\sigma_{\rho}$				-0.562***
				(0.101)
Demand Argentina				
Time	0.038**	0.055**	0.027	0.069***
	(0.018)	(0.022)	(0.018)	(0.016)
$\text{Time}^2/100$	-0.595**	-0.815**	-0.346	-0.916***
	(0.265)	(0.288)	(0.262)	(0.191)
$\text{Time}^3/1000$	0.206*	0.265**	0.140	0.293***
	(0.109)	(0.101)	(0.109)	(0.067)
Demand Brazil				
Time	-0.027**	0.009	-0.014	0.042**
	(0.010)	(0.015)	(0.009)	(0.017)
$\text{Time}^2/100$	0.351***	0.087	0.194*	-0.233
	(0.100)	(0.199)	(0.104)	(0.178)
$\text{Time}^3/1000$	-0.098***	-0.057	-0.055*	0.031
	(0.028)	(0.066)	(0.030)	(0.048)
Demand Chile				
Time	0.007	0.044**	0.081***	0.099***
	(0.012)	(0.015)	(0.013)	(0.014)
$\text{Time}^2/100$	0.030	-0.392**	-0.614***	-0.661***
	(0.151)	(0.178)	(0.161)	(0.126)
$\text{Time}^3/1000$	-0.020	0.082	0.139**	0.130***
	(0.046)	(0.052)	(0.049)	(0.035)
N	96	48	96	192
R^2	0.801	0.642	0.936	0.960

*** 1 percent ** 5 percent * 10 percent. Robust standard errors in parenthesis.
Notes: Each column presents the results of the estimation of the different stages of the model, restricting the sample to workers between the ages of 25 and 55. Column IA shows the OLS estimates of the inverse of the elasticity of substitution between experience and inexperience workers within the low-skilled group ($\sigma_{\theta U}$) (see Equation (5.1)); column IB corresponds to the OLS estimates of the inverse of the elasticity of substitution between experience and inexperience workers within the skilled group ($\sigma_{\theta S}$) (see Equation (5.2)); column II shows the OLS estimates of the inverse of the elasticity of substitution between the two low-skill groups (σ_{δ}), and a second estimate of the inverse of the elasticity of substitution $\sigma_{\theta U}$ (see Equation (5.3)); finally, column III shows the OLS estimates of the inverse of the elasticity of substitution between skilled and unskilled workers (σ_{ρ}), as well as additional estimates from the other elasticities in the model.

Table 8: Model Estimation Results: Part-Time and Full-Time Workers.

	Supply Measure		
	Working Age Pop.	Occupied Pop.	Total Hours Worked
Elasticities			
$-1/\sigma_{\theta_U}$	-0.389***	-0.373***	-0.359***
	(0.044)	(0.043)	(0.043)
$-1/\sigma_{\theta_S}$	-0.171*	-0.171*	-0.125
	(0.094)	(0.092)	(0.090)
$-1/\sigma_{\delta}$	-0.478***	-0.466***	-0.462***
	(0.020)	(0.020)	(0.019)
$-1/\sigma_{\rho}$	-0.432**	-0.467***	-0.372**
	(0.136)	(0.130)	(0.112)
Demand Argentina			
Time	0.040**	0.049**	0.049**
	(0.015)	(0.015)	(0.016)
$\text{Time}^2/100$	-0.414**	-0.544**	-0.501**
	(0.206)	(0.204)	(0.213)
$\text{Time}^3/1000$	0.125	0.165**	0.145*
	(0.080)	(0.078)	(0.080)
$\text{Time}^3/10000$			
Demand Brazil			
Time	0.049**	0.051**	0.058**
	(0.017)	(0.017)	(0.018)
$\text{Time}^2/100$	-0.301	-0.331*	-0.338*
	(0.197)	(0.192)	(0.193)
$\text{Time}^3/1000$	0.049	0.055	0.052
	(0.057)	(0.055)	(0.054)
$\text{Time}^3/10000$			
Demand Chile			
Time	0.103***	0.096***	0.110***
	(0.021)	(0.019)	(0.017)
$\text{Time}^2/100$	-0.702***	-0.691***	-0.736***
	(0.184)	(0.167)	(0.168)
$\text{Time}^3/1000$	0.150**	0.156***	0.155**
	(0.050)	(0.046)	(0.047)
$\text{Time}^3/10000$			
Observations	192	192	192
R^2	0.942	0.943	0.943

*** 1 percent ** 5 percent * 10 percent. Robust standard errors in parenthesis.
Notes: The table reports the third stage estimates of the parameters of the model when we include part-time workers in the construction of the wage series. Each column presents the results using alternative measures of the total labor supply by each group. The first column corresponds to our baseline results; the second column limits the sample to include only employed population; and the final column uses total hours worked.

Table 9: Model Estimation Results: Alternative Production Function

	STEP		
	I	II	III
Elasticities			
$-1/\sigma_\delta$	-0.372***	-0.264***	-0.341***
	(0.026)	(0.011)	(0.014)
$-1/\sigma_\theta$		-0.138**	-0.171***
		(0.045)	(0.043)
$-1/\sigma_\rho$			-0.762***
			(0.047)
Demand Argentina			
Time	0.027*		0.108***
	(0.014)		(0.012)
Time^2/100	-0.002		-0.011***
	(0.002)		(0.002)
Time^3/1000	0.000		0.000***
	(0.000)		(0.000)
Demand Brazil			
Time	-0.003		0.007
	(0.012)		(0.010)
Time^2/100	0.001		0.001
	(0.001)		(0.001)
Time^3/1000	-0.000		-0.000
	(0.000)		(0.000)
Demand Chile			
Time	0.062***		0.084***
	(0.010)		(0.009)
Time^2/100	-0.005***		-0.005***
	(0.001)		(0.001)
Time^3/1000	0.000**		0.000**
	(0.000)		(0.000)
N	336	672	672
R^2	0.973	0.934	0.886

*** 1 percent ** 5 percent * 10 percent. Robust standard errors in parenthesis.
Notes: Each column presents the results of the estimation of the different steps in the alternative model described in the Appendix A.4.

A.2 Data and Variable Construction

The household surveys used in Argentina for the period between 1995 and 2003 are waves of the Encuesta Permanente de Hogares (EPH), collected by the Instituto Nacional de Estadística (INDEC). This survey was replaced by the Encuesta Permanente de Hogares Continiua (EPH-C) after 2003, breaking the series. The transition between the EPH and the EPH-C included changes in the questionnaires and the frequency in which the surveys were collected. The geographical coverage in EPH-C was extended to include additional agglomerates. In order to maintain consistency over the period of study we only use the agglomerates that are present in both surveys. The EPH and the EPH-C are representative for urban areas, but close to 90 percent of the population in Argentina live in urban centers.

The survey used in Brazil is the Pesquisa Nacional por Amostra de Domicilios (PNAD), collected by the Instituto Brasilero de Geografía y Estadísticas (IBGE). The PNAD is a nationally representative survey that has been carried out on a yearly basis since 1967. We use the different waves starting from the year 1990. Due to exceptional circumstances the survey was not collected in 1994 and 2000.

The household survey used for Chile is the Encuesta de Caracterización Socioeconómica Nacional (CASEN). The CASEN is a nationally representative household survey collected by the Ministry of Planning through the Department of Economics at Universidad de Chile. The survey was first implemented in 1987 and was carried out every two years from 1990 to 2000, and every three years thereafter. We use all the waves from 1990 to 2013.

We constructed variables capturing the educational attainment and potential experience of all individuals in the sample. Although the countries we analyze differ in the structure of their educational systems, the SEDLAC project has attempted to homogenize the information from the different countries to make it comparable.[25] We use SEDLAC's coding in the construction of the educational attainment series. In particular, we define five possible levels of educational attainment: i) primary education completed or less; ii) high school incomplete; iii) high school completed; iv) college incomplete; and v) college completed or more. Potential experience is defined as the result of subtracting the total number of years of education completed (plus 6) from the age of the individual.

[25]See CEDLAS and The World Bank (2014) for a detailed description of the SEDLAC database

Although we define five possible levels of educational attainment, we mostly work with three categories: primary or less, high school completed and college completed. Individuals with incomplete levels of education are distributed equally between the previous and next completed level. For example, mean real hourly earnings of workers with college education are calculated as a weighted average between the observed mean wages of this group and the observed mean wages of workers with college incomplete. The weight of the latter group is equal to half of their actual number. This also implies that in the labor supplies used in the model, the supply of workers with primary education completed or less includes half of the total supply of workers of the high school incomplete category. The supply of workers with high school education completed includes both half of the supply of workers with high school incomplete and half of the supply of workers with college incomplete. Finally, the supply of workers with college education completed includes half of the total supply of workers with college incomplete.

Each survey includes a question asking workers for the total monetary income from labor in a reference period. This is the variable that we use throughout the paper to capture labor earnings. The variable is divided by the total number of hours worked to obtain hourly earnings. The series are converted into real terms using the consumer price index of the respective countries.[26] In the main specification we restrict the sample to individuals between the ages of 16 and 65, and only use earnings of full-time workers (individuals working 35 hours or more in the reference week).

The composition adjusted earnings of aggregate groups are constructed using a fixed-weighted average of the different sex-education-experience sub-groups. We first run a regression of log hourly earnings on the full set of covariates that include indicators for the five education categories, seven dummies for potential experience in five-year intervals, and all possible interactions. The regression is estimated separately for males and females in each available country-year. The predicted log wages from these regressions are evaluated for the 70 sub-groups, and a weighted average is estimated when aggregating to broader groups. The weights are equal to the mean employment share of each sub-group across all years.

[26]Due to inconsistencies found in the official Consumer Price Index in Argentina (see Cavallo (2013)), we use the information from PriceStats (`http://www.statestreet.com/ideas/pricestats.html`) to deflate nominal wages in this country.

A.3 Using RIF to Decompose Changes in Distributional Statistics beyond the Mean

Firpo et al. (2007, 2009) allow extending the traditional Oaxaca-Blinder decomposition to distributional statistics beyond the mean. This is achieved through the use of influence functions (IF). Influence functions measure the effect that an infinitesimal amount of "errors" have on a given estimator (Cowell and Victoria-Feser, 1996), but they also have properties that allows us to model the sensitivity of a given unconditional wage quantile to a change in a set of covariates. To see this, let $q_\tau(F_W)$ be τth quantile of the distribution of wages, expressed in terms of the cumulative distribution $F_W(w)$. Define the following mixture distribution:

$$G_{W,\epsilon} = (1-\epsilon)F_W + \epsilon H_W \quad for \quad 0 \leq \epsilon \leq 1 \tag{A.1}$$

where H_W is some perturbation distribution that only puts mass at the value w. In that case, $G_{W,\epsilon}$ is a distribution where, with probability $(1-\epsilon)$, the observation is generated by F_W, and with probability ϵ, the observation takes the arbitrary value of the perturbation distribution. By definition, the influence function corresponds to:

$$IF(w; q_\tau, F_W) = lim_{\epsilon \to 0} \ \frac{q_\tau(G_{W,\epsilon}) - q_\tau(F_W)}{\epsilon} \tag{A.2}$$

where the expression is analogous to the directional derivative of q_τ in the direction of H_W. Analytical expressions for influence functions have been derived for many distributional statistics.[27] The influence function in the case of the τth quantile takes the form:

$$IF(w; q_\tau, F_W) = \frac{\tau - \mathbb{1}[w \leq q_\tau]}{f_W(q_\tau)} \tag{A.3}$$

where $\mathbb{1}[\cdot]$ is an indicator function and f_W is the PDF.[28] Using some of the properties of influence functions, a direct link with the traditional Oaxaca-Blinder approach can be established. In particular, a property that is shared by influence functions is that, by definition, the expectation is equal to zero.

[27] Essama-Nssah and Lambert (2011) provides a comprehensive list of influence functions for different distributional statistics.

[28] Note that the influence function in this case depends on the density. In order to obtain the empirical density the authors propose non-parametric kernel density estimation.

$$\int_{-\infty}^{+\infty} IF(w; q_\tau, F_W)dF(w) = 0 \tag{A.4}$$

Firpo et al. (2009) propose a simple modification in which the quantile is added back to the influence function, resulting in what the authors call the Recentered Influence Function (RIF).

$$RIF(w; q_\tau, F_W) = q_\tau + IF(w; q_\tau, F_W) \tag{A.5}$$

The importance of this transformation lies in the fact that the expectation of the RIF is precisely the quantile q_τ. With this result, Firpo et al. (2009) show that we can model the conditional expectation of the RIF as a linear function of the explanatory variables.

$$E[RIF(w_t; q_\tau, F_{W,t}|X_t)] = X_t'\gamma_t \tag{A.6}$$

Moreover, if we apply the law of iterated expectations to Equation A.6, the end result is an expression that directly relates the impact of changes in the expected values of the covariates on the unconditional quantile q_τ. Note that this result is all that is required to extend the Oaxaca-Blinder decomposition to quantiles, since the basic components of the method are all present in Equation (A.6).

Estimation of Equation (A.6) can be done by OLS, and only requires replacing the dependent variable, $\log w_t$ in the original wage setting model with the RIF of the quantile q_τ. The interpretation of the estimates $\widehat{\gamma}_t$ can be thought of as the effect of a small change in the distribution of X on q_τ, or as linear approximation of the effect of large changes of X on q_τ (Firpo et al., 2007).

A.4 Alternative Model Specification

In this section we present an alternative specification of the production function of the model in Section 4.1. We mostly follow the work of Manacorda et al. (2010), with some small modifications to allow for comparability with our baseline results. Production in the economy is also modeled using a nested constant elasticity of substitution (CES) function with three levels. The first level is identical to the one we use

$$Y_t = \lambda_t \left(L_{Ut}^{\rho} + \alpha_t L_{St}^{\rho}\right)^{1/\rho} \tag{A.7}$$

with the parameters having the same interpretation. In the second level, labor from skilled and unskilled workers is divided into seven potential experience sub-groups, aggregating them with a productivity-weighted CES combination of the form

$$L_{Mt} = \left(\sum_{A=1}^{7} \phi_{MA} L_{MAt}^{\theta}\right)^{1/\theta} \quad \text{for} \quad M = S, U \tag{A.8}$$

where A indexes the potential experience groups; ϕ_{MA} is a time-invariant parameter capturing differences in relative productivities between potential experience groups; and θ is a function of the elasticity of substitution: $\sigma_\theta = \frac{1}{1-\theta}$. Two key differences with our baseline model are worth pointing out. First, the second level of the production function aggregates labor by experience, not by skill sub-groups. The ordering between the second and third levels is then shifted. Second, the model assumes that there are no relative demand/productivity changes between workers with different levels of potential experience. This follows from the assumption that the respective parameters (ϕ_{MA}) are time-invariant, which largely simplifies the estimation.

Finally, the supply of labor from workers with a given potential experience within the unskilled group is composed of a CES combination of labor from the two lower schooling levels

$$L_{UAt} = \left(L_{PAt}^{\delta} + \beta_t L_{HAt}^{\delta}\right)^{1/\delta} \tag{A.9}$$

where P and H denote workers with primary education or less and high school completed, respectively; β_t is a time-variant measure of the relative productivity between the two low education levels; and δ is a function of the elasticity of substitution between the two groups: $\sigma_\delta = \frac{1}{1-\delta}$. Note that β_t is constant across potential experience groups, so relative demand shifts are common in this dimension. Finally, the natural logarithm of the two time-variant parameters (α_t and β_t) are estimated using cubic time trends.

Two differentiating factors between this specification and the work of Manacorda et al. (2010) are worth pointing out. First, we allow for differential demand trends within low skilled workers, which they assume to be constant. Second, we allow for a more flexible specification of the demand trends by fitting a cubic polynomial instead of a linear time trend. This allows us to fit the trend reversals in the skill premiums that we observe in the data.