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# Explaining Latin America’s Decreasing Skilled Wage Premium: Supply, Directed Technical Change, and Demand

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**Explaining Latin America's Decreasing Skilled Wage Premium: Supply, Directed Technical Change, and Demand**

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**ABSTRACT:** Skilled wage premia in Latin American countries have continued declining, albeit more slowly and unevenly. Is the decline driven by demand or supply? This paper proposes a novel adaptation to the demand-supply decomposition framework by incorporating directed technical change (DTC), specifically supply-induced skill-biased technical change that acts to increase the wage premium. DTC counters the traditional substitution effect through which higher education wage attainment reduces the skill premium. Therefore, DTC makes adjusted inferred demand changes less skill biased than the standard framework's traditional inferred demand changes. We apply the framework to ten Latin American countries over three periods, namely the length of the sample, the period between maximum wage premia and 2015, and since 2015. In our baseline results, DTC is quantitatively significant while the substitution effects remain important. Traditional demand shifts were skill biased over the length of the sample including since 2015 but our novel adjusted demand shifts were skill neutral. During the period between maximum premia and 2015, unadjusted demand shifts were skill-neutral and adjusted demand shifts favored unskilled workers. Equivalently, sizeable DTC effects imply wage premia would have fallen significantly faster in the absence of DTC. For an alternative elasticity of 1.25, DTC effects are smaller, supply effects are bigger, and adjustments to demand effects are smaller. For alternative supply measures, the results are relatively robust.

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WORKING PAPERS

# Explaining Latin America's decreasing skilled wage premium: supply, directed technical change, and demand

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# 1. Introduction

Earnings inequality started to decrease since the early 2000s in Latin America after a period of increases. Decreases have been broad based albeit more marked in South America than Central America. The decrease is substantially accounted for by declines in the education wage premium and is the main contributor to overall income inequality declines (Acosta et al (2019), Messina & Silva (2021, henceforth MS)).[1] In the United States, the college wage premium grew substantially until the early 2000s and has been largely unchanged since (Bengali et al, 2025).

To explain the evolution of the wage premium, the literature has drawn on the demand-supply framework of Katz & Murphy (1992, henceforth KM). This framework allows observed developments in education or other wage premia to be accounted for by observed proxies for the relative supply of workers with higher levels of education or other characteristics and a residual that is attributed to unobserved and broadly interpretable demand factors. With varying degrees of emphasis, a consensus has emerged that both demand and supply are needed to explain earnings inequality developments in Latin America, especially for the premium earned by those with at least some tertiary education.

Regarding supply, Manacorda et al (2010) and Fernandez & Messina (2018, henceforth FM) find that much of the decline in the premium is due to a rapid expansion in the supply of workers with more education (though the emphasis is on the secondary-school premium). FM augment the framework by allowing for imperfect substitution between more and less experienced workers. MS also acknowledge an important role for expanding educational attainment.

The framework also attributes an important role to demand. When rises in tertiary education wage premia coincided with rises in relative supply of tertiary education, the implication from the framework is that relative demand for more educated workers also increased (Manacorda et al, 2010). Consistent with this, Acosta et. al. (2019) note that the supply of more educated workers grew relatively consistently before and after the turn of the century, so the reversal of the rise in the wage premium for those with at least some tertiary education must be due to a shift from demand that favored more educated workers to demand that favored less educated workers. FM and MS make similar observations for wage premia for college graduates. Contributions of relative demand drivers include[2] cyclical factors (such as the commodity boom of the early 2000s), trade liberalization, or sectoral shifts, though the demand residual also includes institutional labor market developments such as the minimum wage and formalization (MS).

Technical change is also a potential driver of skill premia. Tinbergen (1975) postulated a "race" between increasing education and what he assumed was inherently skill-biased technical change (SBTC). The skill bias of technologies adopted in developing countries can be largely influenced by the bias of technologies adopted abroad (Berman & Machin, 2000). For example, Gallego (2012) finds a strong link between the degree of skill upgrading in the United States and skill upgrading in Chile that is consistent with the international transmission

[1] The Gini coefficient of inequality rose through the 1990s, peaked in about 2002, and subsequently began to fall since. The strongest has been increases in wages for the poor. Conditional cash transfers have important in some countries. More generally, the tax and transfer system has played a limited role in reducing the Gini (The Economist, 2025).

[2] Although the factors are sometimes used to assess the robustness of results in the demand-supply framework (Manacorda et al, 2010), much of the literature studies such drivers individually using different frameworks.

of the bias of technical change.[3] However, Raveh and Reshef (2016) show that some types of imported technology can lower the skill premium.

An overlooked aspect is that the skill bias of such technology is *endogenous to the supply of skills*. Specifically, if there are more skilled workers, it is more attractive to adopt skill-biased technologies. Thus, the traditional substitution effect in which increased skills availability depresses the skill premium is countered by this *directed technical change* (DTC) effect (Acemoglu, 1998, Kiley, 1999). There is evidence of such factors being at play in developing countries. For example, Caselli and Coleman (2006) find that developing countries apply technologies according to their skill endowments, and Acemoglu & Zilibotti (2001) note that multinationals make technologies available to subsidiaries according to the availability of skilled workers.

The main contribution of this paper is to incorporate DTC in the KM demand-supply framework. Higher skill supply reduces the skill premium through the standard substitution effect but increases it due to technical change that is endogenously skill biased. Both of these drivers are quantified. Because hitherto ignored DTC is hidden in traditional demand estimates, we adjust the quantification of the demand component, though it still contains unobserved exogenous SBTC such as that due to global SBTC.

Section 2 develops the model of DTC that sets how to identify the adjusted demand residual as well as the decomposition of wage premium changes into the various drivers, drawing on Behar (2025). The model shows that the degree of DTC depends on the change in skill supply and on the elasticity of substitution, $\sigma$, between skilled and unskilled labor. For example, for $\sigma = 2$, the DTC effect cancels the substitution effect such that higher skill supply has no effect on the skill premium, which is driven entirely by (adjusted) relative demand.[4] More generally, the presence of DTC means inferred adjusted demand changes are less skill biased / more favorable to unskilled workers than unadjusted demand changes.

Section 3 presents the data and inequality developments for 10 Latin American countries. The data in our sample typically starts in the mid-1990s and we take the opportunity to update developments since 2015, which is about where the analysis in previous studies ends. We focus our analysis on the premium between those who have at least post-secondary education (high education workers) and those who do not (medium and/or low education workers). We document that wage premia (or, more accurately, wage ratios) have continued to decline since 2015. The pace for this recent subset is in line with that observed over the full sample but notably lower than that observed since wage premia were at their peaks. Relative supply has grown relatively consistently.

Section 4 identifies drivers of wage ratios, namely supply, DTC, and two forms of demand: *unadjusted* as per the traditional approach and *adjusted* for DTC. As a corollary, it decomposes wage ratio shifts into contributions from those drivers. Our baseline value for the elasticity of substitution of 1.75 is chosen from existing estimates (Behar, 2025) for its relevance to the region and for consistency with the DTC framework. In the baseline, the traditional approach finds important and consistent downward pressure on wage ratios from increasing relative supply, which operates through the traditional substitution effect. Traditional demand has become more skill

[3] Stagnation in U.S. college premia have been attributed demand factors, which are interpreted as a slowdown in the pace of skill-biased change (Bengali et al, 2025). That wage premium and demand developments are common across Latin American countries and mirror those of the United States is also suggestive of some commonality in the skill bias of labor demand.

[4] In this way, the model helps rationalize the seeming invariance of variable education premium dynamics to the pace of education supply noted above as well as the absence of a cross-section correlation between education attainment and education premia (Banerjee & Duflo, 2005).

biased in recent years at broadly the same pace as for the whole sample period. For periods between when the wage ratio peaked and 2015, traditional demand shifts have been broadly neutral.

Moving beyond the traditional approach, DTC effects are significant and can be thought of as undoing much of supply's substitution effect. DTC therefore requires material adjustments to demand estimates, which become skill neutral (since the start of the sample including since 2015) or unskill biased (since the wage premium maximum). For example, since the start of the sample, the substitution effect on the wage ratio was about -0.9% per year while the DTC effect was about 0.5% per year, which adjusts the skill bias of demand down by 0.5% a year. An alternative interpretation is that, in the absence of DTC, wage ratios would have declined by an additional 0.5% per year.

For an alternative elasticity of 1.25, DTC effects are smaller, supply effects are bigger, and adjustments to demand effects are smaller. As a result, even adjusted demand changes were skill biased over the length of the sample and since 2015 and were skill neutral between the maximum wage premium and 2015. This underscores the importance of the elasticity parameter for ascertaining DTC effects and more generally for the DD-SS framework. Moreover, it's important to note that the demand residual is itself a downward-biased estimate of the true skill bias of demand shifts because the residual includes institutional and labor market contributors to lower wage ratios that our perfectly competitive setup does not capture. For alternative supply measures, the patterns are relatively robust, though the estimated skill bias of demand is slightly higher.

These findings reenforce and update other papers' (e.g., Acosta et al, 2019) findings that changes in wage premium dynamics have been more influenced by changes in demand dynamics than supply dynamics. In particular, our three time periods show slightly more variation in adjusted demand than unadjusted demand and less variation in supply effects when one incorporates DTC.

Section 5 summarizes the findings for this application, reflects on methodological implications for other applications, and suggests complementary enhancements to the framework.

# 2. Model

The basic framework is a CES production structure that, like in other applications, is in the same class as KM. However, it brings in endogenous productivity change in the form of directed technical change (Acemoglu, 2002; Behar, 2025). The key insights from the model can be gleaned from equations 6 and 7, which will underpin the empirical analysis.

Our variant has skilled $y^s$ and unskilled $y^u$ intermediate products combining to make final product Y with $\epsilon > 0$ as the elasticity of substitution between the intermediates. $\beta$ represents demand shifters except the relative productivity of skilled workers, which will be introduced separately.

$$Y = \left[\beta (y^s)^{\frac{\epsilon-1}{\epsilon}} + (y^u)^{\frac{\epsilon-1}{\epsilon}}\right]^{\frac{\epsilon}{\epsilon-1}} \qquad (1)$$

In equilibrium, intermediates have prices $p^s$ and $p^u$ such that:

$$\frac{p^s}{p^u} = \beta \left(\frac{y^s}{y^u}\right)^{-\frac{1}{\epsilon}} \qquad (2)$$

Building on Kiley (1999), each intermediate is produced by a Cobb-Douglas production function with $\alpha$ governing the relative shares of labor and capital: $y^s = T^s(q^s)^\alpha(x^s)^{1-\alpha}$ . $T^s$ is the skill-augmenting productivity term, which can be interpreted as the number of different technologies (Romer, 1990) adopted for use with skilled labor and, as discussed later, is endogenous. $q^s$ is the exogenous quantity of skilled labor in the economy. $x^s$ is the (equal) amount of capital used for each adopted technology. $x^s$ is higher when the price of the skilled intermediate it produces is higher and when there is more skilled labor, which increases the marginal physical product of $x^s$. Thus $x^s = \alpha^{\frac{2}{1-\alpha}}(p^s)^{\frac{1}{1-\alpha}}q^s$. Analogously, $y^u = T^u(q^u)^\alpha(x^u)^{1-\alpha}$.

By substituting for $y^u$ and $y^s$ into (2) and defining the elasticity of substitution between skilled and unskilled labor as $\sigma \equiv \epsilon + \alpha - \epsilon\alpha > 0$, $T \equiv \frac{T^s}{T^u}$, $Q \equiv \frac{q^s}{q^u}$ , and $P \equiv \left(\frac{p^s}{p^u}\right)^{\frac{1}{1-\alpha}}$, we have $P = \beta^{\frac{\epsilon}{\sigma}}(TQ)^{-\frac{1}{\sigma}}$. The skilled wage premium is the product of relative productivity and relative intermediate output prices, $W \equiv \frac{w^s}{w^u} = TP$, such that:

$$W = \beta^{\frac{\epsilon}{\sigma}}T^{\frac{\sigma-1}{\sigma}}Q^{-\frac{1}{\sigma}} \qquad (3)$$

However, the ratio of the number of different skilled to unskilled technologies, *T*, is endogenous. Consider a relatively small open developing economy that does not research its own technologies but acquires them from abroad. As in Behar (2025), but omitting details, equilibrium adoption occurs when the relative cost (*C*) of adoption equals the relative value (*V*) from such adoption. The cost of acquiring a given non-frontier technology is lower when the global technology frontier is more advanced such that the relative cost of skilled technology adoption is inversely related to the skill bias of the global technology frontier, *R*: $C = \frac{1}{R}$. The value of acquiring a technology is proportional to the price of the intermediate it produces and to the amount of labor available to use it: $V = QP$. As a result, $T = \beta^\epsilon Q^{\sigma-1}R^\sigma$. This captures the intuition that technology adoption is more skill biased if the global technology frontier is more skill biased (Berman & Machin, 2000),[5] if demand favors more skill-intensive products, and, crucially, if there are more skilled workers (Kiley, 1999; Acemoglu, 2022). Solving for *T* and substituting into (3) yields:

$$W = \underbrace{\beta^{\left(\frac{\epsilon^2}{\sigma^2}\sigma-1\right)}R^{\sigma-1}}_{adjusted\ demand}\ \underbrace{Q^{-\frac{1}{\sigma}}}_{substitution}\ \underbrace{Q^{\frac{(\sigma-1)^2}{\sigma}}}_{DTC} \qquad (4)$$

Q enters twice. The first Q entry depicts the standard substitution effect by which greater relative availability of skilled labor reduces the wage premium. The second entry depicts the novel DTC effect in which more skilled labor tends to *increase* the skill premium for all $\sigma \neq 1$. *R* captures a dynamic in which a more skill-biased technology frontier tends to increase the skill premium even in non-frontier countries. *R* is specific to our model but will not be separately distinguishable from other demand shifters $\beta$ so we will for empirical purposes subsume both terms in adjusted demand component, *D*.

We briefly review potential demand shifters $\beta$ within *D* that have been discussed in a Latin American context. Standard Heckscher–Ohlin/Stolper–Samuelson (HOSS) predictions include a decrease in relative skilled

[5] Note that this statement about the *bias* of change is different to a statement about the *pace* of change. Also see Behar (2012) for an alternative formal characterization of how the skill bias of global technology and the domestic skill endowment affect the skill bias of technical change.

demand for the region following trade liberalization.[6] But there are many modifications that could nuance the prediction, such as upskilling within industries, while the declines in skill premia started only after a relative slowdown in liberalization, which may be why empirical evidence is ambiguous and context-specific (MS). Guerra-Salas (2018) find that demand shifts to less skilled workers in the 2000s can be partly explained by commodity-driven economic expansion, which drove demand for services.[7] MS find sizeable contributions of between sector-occupation variation to wage inequality dynamics. In these examples, demand shifts could reflect what is made (including sectoral shifts) as well as how it is made. Other cyclical contributors could include the Global Financial Crisis, which reduced income for high earners, and the subsequent recovery, which may have slowed or reversed the reduction in income inequality in some countries (Cord et al 2017).

As a residual, "demand" could also include institutional and labor market drivers not captured by a perfectly-competitive setup. For example, the minimum wage compressed the distribution in some countries.[8] Not accounting for this would bias the true skill bias of demand shifts downwards in these countries. Another example is the region's high informality and the formal-sector wage premium. MS estimate a small contribution of decreasing informality to the decline in wage inequality. They also estimate that the formal-sector wage premium itself has declined. Together, these results suggest that not accounting for informality developments likely slightly biases our estimate of the skill bias of labor demand shifts downward.

The residual could also reflect unobserved (in our data) demographic characteristics. For example, FM show declines in experience premia and assign this to an aging population and demand shifts towards younger workers in the region. Female labor force participation has increased and the wage premium observed for men has increased slightly (Berniell and others, 2024; Casas and others, forthcoming). Such characteristics could matter for precise calculation of true demand drivers because of composition effects and their interplay with education levels.

MS find that wage dispersion between firms has fallen (in contrast to results for developed countries) and contributed considerably to overall declines in wage inequality. Alvarez et al (2018) attribute the declining between-firm dispersion to a declining premium paid by more productive firms. Regarding within-firm dispersion, they observe declining premia for education and other worker characteristics. Haanwinckel (forthcoming) finds that, as workers become more educated, they tend to move to higher-paying firms, which counters the traditional substitution effect.

Having briefly reviewed demand drivers and other developments captured by $\beta$, we combine those with *R* into *D* and take logs:

$$logW = \frac{1}{\sigma}[logD - logQ + (\sigma-1)^2 logQ] \qquad (6a)$$
$$= \frac{1}{\sigma}logD + (\sigma-2)logQ \qquad (6b)$$

[6] HOSS effects can be amplified by directed technical change that is endogenous to the relative price changes that trade liberalization induces (Behar, 2016).

[7] Possible channels for this shift include increased domestic consumption from the income effect and real exchange rate appreciation, which can shift demand to non-tradables.

[8] See Maurizio & Vazquez (2015) for multiple countries. Haanwinckel (forthcoming) studies the interplay between minimum wages, other demand shocks, and educational attainment.

Equation (6a) is like in KM equation 17 but for the final term in Q in which higher skill supply induces SBTC – a DTC effect that generally increases the skill premium and acts against the substitution effect. Combining the DTC and substitution effects in equation (6b) more explicitly shows that whether higher skill supply increases or decreases the skill premium depends on whether $\sigma$ exceeds 2.

For the case of $\sigma = 2$, which as will be discussed is not far from the most applicable estimate, substitution and DTC effects cancel and the quantity term drops out of equation 6. As discussed in Behar (2025), in a cross-section setting, this rationalizes the absence of a correlation between relative skill supply and wage premia (Banerjee & Duflo, 2005), which in more standard models would imply skilled and unskilled labor are perfect substitutes. For the demand-supply framework, wage premia are driven only by demand when $\sigma = 2$. When $\sigma = 1$ there is no DTC effect and equation (6) reverts to the canonical model.[9]

For the purposes of identifying the unobservable demand effect from observable wage premia and labor supply, equation 6 is rearranged:

$$logD = \sigma logW + logQ - (\sigma - 1)^2 logQ \qquad (7a)$$
$$= \sigma logW - \sigma(\sigma - 2) logQ \qquad (7b)$$

Equation (7a) is the same as KM equation 18 but for the last term, which is always (weakly) negative and thus generally tends to reduce the demand component. In the empirical section we will present this "adjusted" demand component alongside the generic KM demand component. When $\sigma = 1$, because there is no DTC effect, there is no adjustment to the demand component.

The above model has been presented in levels but can easily be adjusted to represent (approximate percentage) changes over time. For example, in equation (6b) for $\sigma = 2$, we would assign all observed wage premium changes to skill-biased demand shifts, which could help explain why wage premia increased then decreased despite fairly constant growth in the supply of skills. As a corollary, in equation 7b, all observed wage premium shifts over time would be attributed entirely to changes over time in the skill bias of adjusted demand.

The model abstracts from potential lagged effects of DTC. One important implication is that incorporating DTC into the demand-supply framework is better suited for longer-horizon changes.[10] Moreover, Acemoglu (1998) assumes the substitution effect operates over the short run and the directed technology effect operates over the long run, such that increases in U.S. wage premia were not due to slowing skill supply growth but the lagged effects of earlier skill supply growth. Such dynamics have informed empirical specifications with higher-frequency data (Behar, 2025; Serrano & Timmer, 2002).

[9] See Acemoglu (2002) for details on why and on how the transmission channel depends on whether $\sigma$ is greater or smaller than 1.

[10] The informal sector typically absorbs new technologies more slowly than the formal sector. Although this does not mean the *bias* of technology would differ across sectors in steady state, the DTC effect could take longer in the informal sector.

# 3. Data and Updated Wage Premium Developments

Following earlier studies (Acosta et al (2019) and MS), we use the harmonized Socioeconomic Database for Latin America and the Caribbean (SEDLAC) made available by the World Bank and the Center for Distributive, Labor and Social Studies (CEDLAS). Our sample comprises a subset of ten Latin American countries, whose inclusion uses judgement based on the length and recency of the time series as well as geographical representation and the number of methodological changes.

The core data are the educational structure of the adult population and the wages for each of those groups. Educational structure consists of shares in the adult population[11] with "low" (up to 8 years), "medium" (9-13 years), and "high" (more than 13 years) levels of formal education. High levels correspond closely to having at least completed secondary and possibly some tertiary education. Educational structure is the measure of supply/quantity. Hourly wage data are available for the corresponding education levels.

Our analysis will focus on the distinction between those who have high education levels (skilled labor) and those who don't (unskilled labor). We do so by aggregating the medium and low education groups.[12] For supply, we create efficiency units by weighting the share of medium education workers by the medium/low wage ratio, such that this group is in low-education equivalents. We then calculate the ratio of high education (skilled) to the combined medium and low education (unskilled) groups. We calculate the unskilled wage aggregate as the quantity-weighted average of medium and low wages and then calculate the ratio of the skilled wage to the unskilled wage. This relatively simple aggregation neither estimates predicted values for quantities or wages nor disaggregates by other characteristics.[13] However, because the unskilled aggregate uses wage information, which could create a circularity concern, we also report results for unweighted aggregates of medium and low education workers and wages and where we show low and medium education categories separately.

Our analysis will distinguish between various points in time, which in most cases will be country-specific due to data availability or data values and are detailed in the tables that will feature in the next section. The first point is the start of the time series in our sample. The second is whenever the maximum wage ratio is observed,[14] the third is the year 2015 (or nearest observable data point), which is approximately the latest data that was available in the previously cited relatively recent papers. The third and final point is the most recent data. We then present analysis covering the full length of the sample, a subset between the maximum wage ratio and 2015 ("max-to-2015"), and a subset since 2015.

[11] Results from earlier studies such as Acosta et al (2019) and MS indicate results are robust to alternative measures such as the labor force, employment, or hours worked.

[12] Formally, this can be rationalized through a CES sub aggregate for $y^u$ in which medium and low education workers are perfect substitutes and use the same technologies although they have differing productivities.

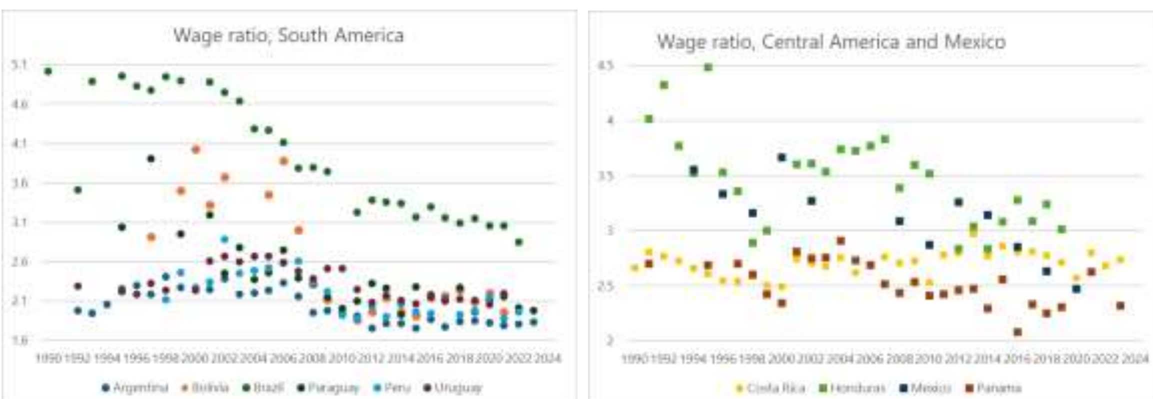
[13] KM construct multiple efficiency units. Acosta et al (2019) construct their efficiency units by dividing the population into 24 cells according to education, gender, and experience. MS construct 40 cells from similar characteristics. FM focus their analysis on males but allow for imperfect substitution across experience types. Acosta et al (ibid) estimate wage premia using Mincerian regressions.

[14] In Panama, we took the second highest as the highest appeared to be an outlier.

In broad strokes, wage ratios are on average lower in the latest data than they were around thirty years ago and since 2015. The pace of decline in the last few years is low when compared to that since the maxima were observed but is not low when compared to the start of the series. Specifically, the average/median fall in the wage ratio was 0.02 per year since the country-specific start of the time series, 0.06-0.07 per year between each country's maximum and 2015, and 0.02-0.03 per year since 2015. Log changes indicate the (approximate) annual average/median change was -0.36%/-0.32% since the start of the series and –1.03%/-0.83% between the country maxima and 2015. Since 2015, the average annual change was -0.48% and the median change was -0.24%.

Figure 1 presents country-specific wage ratios, distinguishing between South America (left chart) and Central America plus Mexico (CAM, right chart). For South America, we replicate the hump shape identified in the literature. Wage premia increased in the 1990s, peaked around the early 2000s, and decreased in the first decade that followed. The subsequent decade has indicated a more mixed picture and generally slower declines. CAM does not have the hump but premia have generally declined since the start of the time-series. Costa Rica is the only country in our sample where wage premia are higher than they were thirty years ago but, in all CAM countries, the premium has declined since 2015. In both figures, the ratio seems to be converging to a value of just above 2.[15]

**Figure 1: Wage ratios between skilled (high education) and aggregated unskilled labor.**




Annex 1 presents analogous charts for the disaggregated skill categories. On average, the high/medium ratio was unchanged since the start of the time series, fell by about 0.9% per year between the country peaks and 2015,[16] and fell by 0.2% per year since 2015, though the median country experienced a marginal increase since 2015. This suggests much of the overall decline in the premium between skilled and aggregated unskilled workers was driven by the premium with respect to low-education workers. Indeed, the high/low premium fell on average by 0.4% per year since the start of the time series, 1.2% per year between country peaks and 2015, and by 0.6% per year since 2015, reflecting broad-based declines. For completeness, we note that the medium/low premium has also generally declined, which suggests that increases in wages for those with low education continue to be important contributors to reductions in wage inequality.[17]

[15] Whether there might be some equilibrium or 'natural' ratio or limit is an interesting question that lies beyond the scope of this paper.

[16] In Costa Rica, the maximum for this ratio occurred only after 2015.

[17] We do not focus on this ratio because we conjecture that SBTC including DTC is more relevant for explaining wage premia that involve highly educated workers.

Regarding developments in educational structure, the main message is that the supply of skilled workers has continued to grow at a broadly consistent rate.[18] The average/median pace since 2015 of 1.6% per year is in line with that since the start of the data (1.5%) and slightly exceeds that observed since wage premia peaked (1.2-1.4%). Increases including marginal accelerations are observable when disaggregating into high/medium and high/low labor ratios, though the latter ratio has increased more rapidly.[19]

# 4. Identifying Demand and Decomposing Wage Ratio Developments

This section presents results identifying drivers of wage ratios including DTC and adjusted labor demand shifts. It does so across multiple time periods and checks for implications of using different measures of unskilled labor and different values for the elasticity of substitution.

Regarding existing estimates of the elasticity of substitution, a meta study performed by Havranek et al (2024) reports a mean value of 2 for developing countries. However, this is not an appropriate reference value under DTC. When reinterpreting existing work under the DTC framework – specifically that the regression coefficient on skill supply is as in equation 6b and not the inverse of $\sigma$, then the Havranek et al (ibid) mean is about 1.5 and the interquartile range is [1.3;1.8]. Using the SEDLAC data used for this paper, Behar (2025: Table 4) estimates values of 1.6-1.8 (though some values for Central America are closer to 2).[20] This justifies a value of $\sigma$=1.75 for our analysis despite being near the top of the interquartile range. However, FM estimate a coefficient that under our framework implies 1.2 for three South American countries, so we briefly discuss how results change for $\sigma$=1.25 (near the bottom of the interquartile range).

**Baseline elasticity (1.75)**

For $\sigma = 1.75$ and comparing workers with high education to those with medium or low education, Table 1 presents the data on wage ratios and supply as well as calculated values for traditional demand, DTC, and adjusted demand (as per equation 7a). We show results for each country and for the average and median. The year column indicates the reference year for the country-specific start of the data, maximum wage ratio, whether we use 2015 data or a nearby year, and end of the data.[21] These rows present values in levels. Subsequent rows for each country/median/average present cumulative changes between reference years. Recall that the length of time is not constant for each period across countries.

[18] We abstract here from how much of this is due to the composition of new labor market entrants (i.e. younger workers who stayed in school for longer) and how much is due to the composition of those exiting the labor force (i.e. retirees who has lower education levels). Behar (2012) models such transition dynamics using a Markov process.

[19] Considering individual components, the average share of the labor force with low education dropped by 29 percent over the length of the sample, of which 16 percent is accounted for by the increase in medium education and 13 precent is accounted for by the increase in high education. Since 2015, the share of low education fell from 43 to 36 percent, the share of medium rose from 36 to 40 percent, and the share with high education rose from 21 to 24 percent.

[20] One advantage of using the DTC framework for estimation is the much lower volatility in σ estimates, as explained in Behar (2025).

[21] In some cases, a year may have more than one data point, which may be referenced by a suffix.

**Table 1: Wages, supply, demand, and directed technical change ($\sigma = 1.75$, high vs low and medium).**

| | Year | Wage Ratio | Log Wage Ratio | Labor Force Ratio | Log Labor Force Ratio (relative supply) | Katz Murphy Log Demand Ratio | Log Directed Technical Change | Adjusted Log Demand Ratio |
|---|---|---|---|---|---|---|---|---|
| **Argentina** | | | | | | | | |
| Data start | 1992 | 1.98 | 0.30 | 0.19 | -0.72 | -0.20 | -0.40 | 0.21 |
| Ratio/year max | 1998 | 2.44 | 0.39 | 0.22 | -0.66 | 0.02 | -0.37 | 0.39 |
| 2015 | 2016-II | 1.86 | 0.27 | 0.39 | -0.41 | 0.06 | -0.23 | 0.29 |
| Data end | 2023-I | 1.83 | 0.26 | 0.45 | -0.34 | 0.12 | -0.19 | 0.31 |
| *End-start* | *31* | *-0.15* | *-0.03* | *0.26* | *0.37* | *0.31* | *0.21* | *0.10* |
| *2015-max* | *18* | *-0.58* | *-0.12* | *0.17* | *0.25* | *0.05* | *0.14* | *-0.10* |
| *End-2015* | *7* | *-0.03* | *-0.01* | *0.06* | *0.07* | *0.05* | *0.04* | *0.02* |
| **Bolivia** | | | | | | | | |
| Data start | 1997 | 2.92 | 0.47 | 0.17 | -0.78 | 0.03 | -0.44 | 0.47 |
| Ratio/year max | 2000 | 4.02 | 0.60 | 0.17 | -0.78 | 0.28 | -0.44 | 0.72 |
| 2015 | 2015 | 1.91 | 0.28 | 0.28 | -0.56 | -0.07 | -0.31 | 0.25 |
| Data end | 2021 | 1.95 | 0.29 | 0.37 | -0.43 | 0.08 | -0.24 | 0.32 |
| *End-start* | *24* | *-0.96* | *-0.17* | *0.21* | *0.35* | *0.05* | *0.20* | *-0.15* |
| *2015-max* | *15* | *-2.11* | *-0.32* | *0.11* | *0.22* | *-0.35* | *0.12* | *-0.47* |
| *End-2015* | *6* | *0.05* | *0.01* | *0.10* | *0.13* | *0.15* | *0.07* | *0.07* |
| **Brazil** | | | | | | | | |
| Data start | 1981 | 4.86 | 0.69 | 0.05 | -1.27 | -0.07 | -0.72 | 0.64 |
| Ratio/year max | 1982 | 5.66 | 0.75 | 0.05 | -1.33 | -0.01 | -0.75 | 0.74 |
| 2015 | 2015 | 3.63 | 0.56 | 0.16 | -0.79 | 0.19 | -0.44 | 0.64 |
| Data end | 2022 | 2.84 | 0.45 | 0.24 | -0.62 | 0.18 | -0.35 | 0.52 |
| *End-start* | *41* | *-2.02* | *-0.23* | *0.19* | *0.66* | *0.25* | *0.37* | *-0.12* |
| *2015-max* | *33* | *-2.02* | *-0.19* | *0.12* | *0.54* | *0.20* | *0.30* | *-0.10* |
| *End-2015* | *7* | *-0.79* | *-0.11* | *0.08* | *0.17* | *-0.01* | *0.10* | *-0.11* |
| **Costa Rica** | | | | | | | | |
| Data start | 1989 | 2.59 | 0.41 | 0.08 | -1.07 | -0.35 | -0.60 | 0.25 |
| Ratio/year max | 2013 | 2.97 | 0.47 | 0.21 | -0.67 | 0.15 | -0.38 | 0.53 |
| 2015 | 2015 | 2.86 | 0.46 | 0.21 | -0.68 | 0.12 | -0.38 | 0.50 |
| Data end | 2023 | 2.74 | 0.44 | 0.26 | -0.58 | 0.19 | -0.33 | 0.51 |
| *End-start* | *34* | *0.15* | *0.02* | *0.18* | *0.49* | *0.53* | *0.28* | *0.26* |
| *2015-max* | *2* | *-0.11* | *-0.02* | *0.00* | *-0.01* | *-0.03* | *0.00* | *-0.03* |
| *End-2015* | *8* | *-0.12* | *-0.02* | *0.05* | *0.10* | *0.07* | *0.06* | *0.01* |
| **Honduras** | | | | | | | | |
| Data start | 1991 | 4.02 | 0.60 | 0.03 | -1.49 | -0.43 | -0.84 | 0.41 |
| Ratio/year max | 1995 | 4.49 | 0.65 | 0.03 | -1.48 | -0.34 | -0.83 | 0.49 |
| 2015 | 2015 | 3.08 | 0.49 | 0.07 | -1.13 | -0.28 | -0.64 | 0.36 |
| Data end | 2019 | 3.01 | 0.48 | 0.09 | -1.03 | -0.19 | -0.58 | 0.39 |
| *End-start* | *28* | *-1.01* | *-0.13* | *0.06* | *0.45* | *0.23* | *0.25* | *-0.02* |
| *2015-max* | *20* | *-1.40* | *-0.16* | *0.04* | *0.34* | *0.06* | *0.19* | *-0.13* |
| *End-2015* | *4* | *-0.07* | *-0.01* | *0.02* | *0.10* | *0.08* | *0.06* | *0.03* |
| **Mexico** | | | | | | | | |
| Data start | 1994 | 3.56 | 0.55 | 0.11 | -0.97 | 0.00 | -0.54 | 0.54 |
| Ratio/year max | 2000 | 3.67 | 0.56 | 0.14 | -0.87 | 0.12 | -0.49 | 0.61 |
| 2015 | 2016 | 2.85 | 0.46 | 0.20 | -0.71 | 0.09 | -0.40 | 0.49 |
| Data end | 2020 | 2.47 | 0.39 | 0.23 | -0.64 | 0.05 | -0.36 | 0.41 |
| *End-start* | *26* | *-1.09* | *-0.16* | *0.12* | *0.33* | *0.05* | *0.19* | *-0.13* |
| *2015-max* | *16* | *-0.82* | *-0.11* | *0.06* | *0.16* | *-0.03* | *0.09* | *-0.12* |
| *End-2015* | *4* | *-0.38* | *-0.06* | *0.03* | *0.07* | *-0.04* | *0.04* | *-0.08* |
| **Panama** | | | | | | | | |
| Data start | 1989 | 2.70 | 0.43 | 0.13 | -0.88 | -0.13 | -0.50 | 0.37 |
| Ratio/year max | 2004 | 2.91 | 0.46 | 0.20 | -0.69 | 0.12 | -0.39 | 0.51 |
| 2015 | 2015 | 2.56 | 0.41 | 0.30 | -0.52 | 0.19 | -0.29 | 0.49 |
| Data end | 2023 | 2.32 | 0.37 | 0.34 | -0.47 | 0.17 | -0.26 | 0.43 |
| *End-start* | *34* | *-0.38* | *-0.07* | *0.21* | *0.41* | *0.30* | *0.23* | *0.07* |
| *2015-max* | *11* | *-0.35* | *-0.06* | *0.10* | *0.17* | *0.07* | *0.10* | *-0.02* |
| *End-2015* | *8* | *-0.24* | *-0.04* | *0.04* | *0.05* | *-0.02* | *0.03* | *-0.05* |
| **Paraguay** | | | | | | | | |
| Data start | 1995 | 3.04 | 0.48 | 0.07 | -1.14 | -0.29 | -0.64 | 0.35 |
| Ratio/year max | 1997 | 3.90 | 0.59 | 0.08 | -1.09 | -0.06 | -0.61 | 0.56 |
| 2015 | 2015 | 2.28 | 0.36 | 0.24 | -0.63 | 0.00 | -0.35 | 0.35 |
| Data end | 2023 | 1.97 | 0.29 | 0.37 | -0.43 | 0.09 | -0.24 | 0.33 |
| *End-start* | *28* | *-1.07* | *-0.19* | *0.30* | *0.71* | *0.38* | *0.40* | *-0.02* |
| *2015-max* | *18* | *-1.63* | *-0.23* | *0.16* | *0.47* | *0.06* | *0.26* | *-0.21* |
| *End-2015* | *8* | *-0.31* | *-0.06* | *0.13* | *0.20* | *0.09* | *0.11* | *-0.02* |
| **Peru** | | | | | | | | |
| Data start | 1998 | 2.11 | 0.33 | 0.19 | -0.72 | -0.15 | -0.40 | 0.26 |
| Ratio/year max | 2003b | 3.11 | 0.49 | 0.22 | -0.66 | 0.21 | -0.37 | 0.58 |
| 2015 | 2015 | 1.96 | 0.29 | 0.27 | -0.57 | -0.06 | -0.32 | 0.26 |
| Data end | 2022 | 1.96 | 0.29 | 0.29 | -0.53 | -0.02 | -0.30 | 0.28 |
| *End-start* | *24* | *-0.16* | *-0.03* | *0.10* | *0.18* | *0.12* | *0.10* | *0.02* |
| *2015-max* | *12* | *-1.16* | *-0.20* | *0.05* | *0.08* | *-0.27* | *0.05* | *-0.32* |
| *End-2015* | *7* | *0.00* | *0.00* | *0.03* | *0.04* | *0.04* | *0.02* | *0.02* |
| **Uruguay** | | | | | | | | |
| Data start | 1989 | 2.33 | 0.37 | 0.06 | -1.19 | -0.55 | -0.67 | 0.12 |
| Ratio/year max | 2005 | 2.67 | 0.43 | 0.19 | -0.71 | 0.03 | -0.40 | 0.43 |
| 2015 | 2015 | 2.06 | 0.31 | 0.21 | -0.67 | -0.12 | -0.38 | 0.26 |
| Data end | 2020 | 2.06 | 0.31 | 0.25 | -0.60 | -0.05 | -0.34 | 0.28 |
| *End-start* | *31* | *-0.27* | *-0.05* | *0.19* | *0.59* | *0.49* | *0.33* | *0.16* |
| *2015-max* | *10* | *-0.61* | *-0.11* | *0.02* | *0.04* | *-0.15* | *0.02* | *-0.18* |
| *End-2015* | *5* | *0.00* | *0.00* | *0.04* | *0.07* | *0.07* | *0.04* | *0.03* |
| **Average** | | | | | | | | |
| *End-start* | 30 | -0.70 | -0.10 | 0.18 | 0.45 | 0.27 | 0.26 | 0.02 |
| *2015-max* | 16 | -1.08 | -0.15 | 0.08 | 0.23 | -0.04 | 0.13 | -0.17 |
| *End-2015* | 6 | -0.19 | -0.03 | 0.06 | 0.10 | 0.05 | 0.06 | -0.01 |
| **Median** | | | | | | | | |
| *End-start* | 30 | -0.67 | -0.10 | 0.19 | 0.43 | 0.27 | 0.24 | 0.00 |
| *2015-max* | 16 | -0.99 | -0.14 | 0.08 | 0.19 | 0.01 | 0.11 | -0.13 |
| *End-2015* | *7* | *-0.10* | *-0.01* | *0.05* | *0.09* | *0.06* | *0.05* | *0.01* |

Focusing on median and average changes near the bottom of Table 1, the decrease in the wage ratio and increase in skill supply discussed earlier are shown in columns 3-6. Our analysis centers on the last 3 columns (columns 7-9). On average, traditional / Katz Murphy log demand rose by 0.27, which means it became about 27% more skill biased over the length of the sample (30 years on average). However, DTC had a log difference of 0.26 or about 26%, which when subtracted from traditional demand implies adjusted demand shifts were broadly skill neutral (0.02). There is a similar dynamic since 2015, where traditional demand was skill biased (0.05 over 6 years) but adjusted demand was neutral (-0.01). Between the maximum wage premium and 2015 ("max-to-2015"), traditional demand shifts have been neutral while adjusted demand indicates shifts (-0.17 on average) in favor of unskilled workers.

Table 2 presents the decomposition of the wage ratio and its evolution as per equation 6a. Alongside traditional demand and supply / substitution effects on wages, it presents demand effects on wages that are adjusted for DTC. Unlike in Table 1, changes are approximately annualized by dividing the cumulative change by the number of years. The log wage ratio column underscores that declines since 2015 have been broadly as fast as over the entire sample but notably slower than during max-to-2015.

The traditional decomposition approach indicates that, since the start, the average annual decline of 0.36% in the wage ratio was due to increased supply reducing the wage ratio by 0.86% per year (substitution effect alone) being partially offset by traditional relative demand for skilled workers increasing by 0.50% per year. In our approach, netting out DTC effects of 0.48% per year, which acts to increase the wage ratio, the adjusted demand effect is 0.02% per year and consistent with neutral demand shifts. Equivalently, the average DTC component is about the same size as the unadjusted demand component.

During max-to-2015, the main drivers of the faster wage ratio declines were not especially fast supply increases but large unskilled-biased shifts in adjusted demand. Traditional demand shifts are slightly unskilled biased on average and skill neutral for the median, so we interpret this as broadly skill neutral. Since 2015, the deceleration in wage compression despite a bigger supply (substitution) effect is primarily due to demand shifts that by our adjusted demand measure ceased favoring unskilled workers (and by the traditional measure became skill biased again). These findings reenforce and update other papers' findings that changes in wage premium dynamics have been more influenced by changes in demand dynamics than supply dynamics. In particular, our three time periods show slightly more variation in adjusted demand than unadjusted demand and less variation in net supply effects that incorporates DTC.

Although not shown explicitly in the table, the netting out effect due to DTC can simultaneously be interpreted as reducing the substitution effect from supply. For example, over the whole sample period, the net reduction in the wage ratio from supply is 0.86%-0.48%=0.38% per year. In other words, in the absence of DTC, the wage ratio would have declined by an additional 0.48% per year over the course of the sample. For the max-to-2015 and post-2015 samples, the no-DTC counterfactual declines in wage ratios would have been an additional 0.39% and 0.52% per year, respectively.

**Table 2: Contributions to Wage Ratios ($\sigma = 1.75$, high vs low and medium).**

| | Year | Log Wage Ratio | Unadjusted Log Demand | Log Supply (substitution) | Log Directed Technical Change | Adjusted Log Demand |
|---|---|---|---|---|---|---|
| **Argentina** | | | | | | |
| Data start | 1992 | 0.30 | -0.11 | 0.41 | -0.23 | 0.12 |
| Ratio/year max | 1998 | 0.39 | 0.01 | 0.38 | -0.21 | 0.22 |
| 2015 | 2016-II | 0.27 | 0.04 | 0.23 | -0.13 | 0.17 |
| Data end | 2023-I | 0.26 | 0.07 | 0.20 | -0.11 | 0.18 |
| *End-start (annualized)* | 31 | -0.1% | *0.6%* | *-0.7%* | *0.4%* | *0.2%* |
| *2015-max (annualized)* | 18 | -0.7% | *0.1%* | *-0.8%* | *0.4%* | *-0.3%* |
| *End-2015 (annualized)* | 7 | -0.1% | *0.4%* | *-0.5%* | *0.3%* | *0.1%* |
| **Bolivia** | | | | | | |
| Data start | 1997 | 0.47 | 0.02 | 0.45 | -0.25 | 0.27 |
| Ratio/year max | 2000 | 0.60 | 0.16 | 0.44 | -0.25 | 0.41 |
| 2015 | 2015 | 0.28 | -0.04 | 0.32 | -0.18 | 0.14 |
| Data end | 2021 | 0.29 | 0.05 | 0.25 | -0.14 | 0.18 |
| *End-start (annualized)* | 24 | -0.7% | *0.1%* | *-0.8%* | *0.5%* | *-0.4%* |
| *2015-max (annualized)* | 15 | -2.2% | *-1.3%* | *-0.8%* | *0.5%* | *-1.8%* |
| *End-2015 (annualized)* | 6 | 0.2% | *1.4%* | *-1.2%* | *0.7%* | *0.7%* |
| **Brazil** | | | | | | |
| Data start | 1981 | 0.69 | -0.04 | 0.73 | -0.41 | 0.37 |
| Ratio/year max | 1982 | 0.75 | 0.00 | 0.76 | -0.43 | 0.42 |
| 2015 | 2015 | 0.56 | 0.11 | 0.45 | -0.25 | 0.36 |
| Data end | 2022 | 0.45 | 0.10 | 0.35 | -0.20 | 0.30 |
| *End-start (annualized)* | 41 | -0.6% | *0.3%* | *-0.9%* | *0.5%* | *-0.2%* |
| *2015-max (annualized)* | 33 | -0.6% | *0.3%* | *-0.9%* | *0.5%* | *-0.2%* |
| *End-2015 (annualized)* | 7 | -1.5% | *-0.1%* | *-1.4%* | *0.8%* | *-0.9%* |
| **Costa Rica** | | | | | | |
| Data start | 1989 | 0.41 | -0.20 | 0.61 | -0.34 | 0.15 |
| Ratio/year max | 2013 | 0.47 | 0.09 | 0.39 | -0.22 | 0.30 |
| 2015 | 2015 | 0.46 | 0.07 | 0.39 | -0.22 | 0.29 |
| Data end | 2023 | 0.44 | 0.11 | 0.33 | -0.19 | 0.29 |
| *End-start (annualized)* | 34 | 0.1% | *0.9%* | *-0.8%* | *0.5%* | *0.4%* |
| *2015-max (annualized)* | 2 | -0.8% | *-1.0%* | *0.1%* | *-0.1%* | *-0.9%* |
| *End-2015 (annualized)* | 8 | -0.2% | *0.5%* | *-0.7%* | *0.4%* | *0.1%* |
| **Honduras** | | | | | | |
| Data start | 1991 | 0.60 | -0.24 | 0.85 | -0.48 | 0.23 |
| Ratio/year max | 1995 | 0.65 | -0.19 | 0.85 | -0.48 | 0.28 |
| 2015 | 2015 | 0.49 | -0.16 | 0.65 | -0.36 | 0.21 |
| Data end | 2019 | 0.48 | -0.11 | 0.59 | -0.33 | 0.22 |
| *End-start (annualized)* | 28 | -0.4% | *0.5%* | *-0.9%* | *0.5%* | *0.0%* |
| *2015-max (annualized)* | 20 | -0.8% | *0.2%* | *-1.0%* | *0.6%* | *-0.4%* |
| *End-2015 (annualized)* | 4 | -0.3% | *1.2%* | *-1.5%* | *0.8%* | *0.4%* |
| **Mexico** | | | | | | |
| Data start | 1994 | 0.55 | 0.00 | 0.55 | -0.31 | 0.31 |
| Ratio/year max | 2000 | 0.56 | 0.07 | 0.49 | -0.28 | 0.35 |
| 2015 | 2016 | 0.46 | 0.05 | 0.40 | -0.23 | 0.28 |
| Data end | 2020 | 0.39 | 0.03 | 0.36 | -0.20 | 0.23 |
| *End-start (annualized)* | 26 | -0.6% | *0.1%* | *-0.7%* | *0.4%* | *-0.3%* |
| *2015-max (annualized)* | 16 | -0.7% | *-0.1%* | *-0.6%* | *0.3%* | *-0.4%* |
| *End-2015 (annualized)* | 4 | -1.6% | *-0.5%* | *-1.0%* | *0.6%* | *-1.1%* |
| **Panama** | | | | | | |
| Data start | 1989 | 0.43 | -0.07 | 0.50 | -0.28 | 0.21 |
| Ratio/year max | 2004 | 0.46 | 0.07 | 0.40 | -0.22 | 0.29 |
| 2015 | 2015 | 0.41 | 0.11 | 0.30 | -0.17 | 0.28 |
| Data end | 2023 | 0.37 | 0.10 | 0.27 | -0.15 | 0.25 |
| *End-start (annualized)* | 34 | -0.2% | *0.5%* | *-0.7%* | *0.4%* | *0.1%* |
| *2015-max (annualized)* | 11 | -0.5% | *0.4%* | *-0.9%* | *0.5%* | *-0.1%* |
| *End-2015 (annualized)* | 8 | -0.5% | *-0.2%* | *-0.4%* | *0.2%* | *-0.4%* |
| **Paraguay** | | | | | | |
| Data start | 1995 | 0.48 | -0.17 | 0.65 | -0.37 | 0.20 |
| Ratio/year max | 1997 | 0.59 | -0.03 | 0.62 | -0.35 | 0.32 |
| 2015 | 2015 | 0.36 | 0.00 | 0.36 | -0.20 | 0.20 |
| Data end | 2023 | 0.29 | 0.05 | 0.25 | -0.14 | 0.19 |
| *End-start (annualized)* | 28 | -0.7% | *0.8%* | *-1.4%* | *0.8%* | *0.0%* |
| *2015-max (annualized)* | 18 | -1.3% | *0.2%* | *-1.5%* | *0.8%* | *-0.7%* |
| *End-2015 (annualized)* | 8 | -0.8% | *0.6%* | *-1.4%* | *0.8%* | *-0.2%* |
| **Peru** | | | | | | |
| Data start | 1998 | 0.33 | -0.08 | 0.41 | -0.23 | 0.15 |
| Ratio/year max | 2003b | 0.49 | 0.12 | 0.38 | -0.21 | 0.33 |
| 2015 | 2015 | 0.29 | -0.04 | 0.33 | -0.18 | 0.15 |
| Data end | 2022 | 0.29 | -0.01 | 0.31 | -0.17 | 0.16 |
| *End-start (annualized)* | 24 | -0.1% | *0.3%* | *-0.4%* | *0.2%* | *0.0%* |
| *2015-max (annualized)* | 12 | -1.7% | *-1.3%* | *-0.4%* | *0.2%* | *-1.5%* |
| *End-2015 (annualized)* | 7 | 0.0% | *0.3%* | *-0.3%* | *0.2%* | *0.1%* |
| **Uruguay** | | | | | | |
| Data start | 1989 | 0.37 | -0.31 | 0.68 | -0.38 | 0.07 |
| Ratio/year max | 2005 | 0.43 | 0.02 | 0.41 | -0.23 | 0.25 |
| 2015 | 2015 | 0.31 | -0.07 | 0.38 | -0.22 | 0.15 |
| Data end | 2020 | 0.31 | -0.03 | 0.34 | -0.19 | 0.16 |
| *End-start (annualized)* | 31 | -0.2% | *0.9%* | *-1.1%* | *0.6%* | *0.3%* |
| *2015-max (annualized)* | 10 | -1.1% | *-0.9%* | *-0.2%* | *0.1%* | *-1.0%* |
| *End-2015 (annualized)* | 5 | 0.0% | *0.8%* | *-0.8%* | *0.4%* | *0.3%* |
| **Average** | | | | | | |
| *End-start (annualized)* | 30 | -0.36% | 0.50% | -0.86% | 0.48% | 0.02% |
| *2015-max (annualized)* | 16 | -1.03% | -0.34% | -0.70% | 0.39% | -0.73% |
| *End-2015 (annualized)* | 6 | -0.48% | 0.44% | -0.92% | 0.52% | -0.08% |
| **Median** | | | | | | |
| *End-start (annualized)* | 30 | -0.32% | 0.49% | -0.83% | 0.47% | 0.00% |
| *2015-max (annualized)* | 16 | -0.83% | 0.01% | -0.82% | 0.46% | -0.54% |
| *End-2015 (annualized)* | 7 | -0.24% | 0.46% | -0.89% | 0.50% | 0.10% |

**Figure 2: Wage drivers and decomposition analysis ($\sigma = 1.75$, high vs low and medium).**

Figure 2 reproduces the country-specific information from Tables 1 and 2 to facilitate visualization. One additional piece of information is dots that estimate how much of the changes in the wage ratio over time may be due to changes in the survey method or coverage.[22] Where there were such effects, they were generally negligible and in a couple of cases acted to increase the wage ratio. In those cases, this means that observed wage ratio decreases understate true wage ratio decreases, and that demand shifts have been even less skill biased than implied by our results. Because of the limited importance of method/coverage changes, we do not modify demand and other variables.

In the top left chart of Figure 2, traditional demand shifts were positive over the length of the sample for all ten countries, though the shifts were close to neutral in Bolivia and Mexico. Adjusted demand became unskilled biased in 3 cases and broadly neutral in another 3 cases. Paraguay is an example with a big rise in skill supply, which for the observed decline in the wage ratio implies skill-biased traditional demand changes. However, sizable supply increases generate sizeable DTC for sufficiently high $\sigma$. (Recall that, for $\sigma = 2$, this effect would exactly match the standard relative supply increase.) DTC is of a similar magnitude to traditional demand, which implies broadly neutral adjusted demand shifts. Over the same period, the top right chart provides a decomposition analysis that permits a comparison of the relative importance of the factors. Although standalone substitution effects would under the traditional approach be the biggest contributor to the decrease in the wage premium in all countries, the resulting DTC effect is also important. As a counterweight to traditional supply that increases the wage ratio, DTC is consistently more important than adjusted demand.

The middle two charts present results for max-to-2015. Although traditional demand presents a mixed picture, adjusted demand is negative for all ten countries and sufficiently large to be interpreted as unskilled-biased in most cases. In many of those cases, adjusted demand is sufficiently unskilled-biased to make a bigger contribution to the declining wage ratio than the traditional substitution effect. Although not explicitly shown, there are many cases where adjusted demand drove the premium down by considerably more than supply effects net of DTC. The bottom two charts show developments since 2015. While supply continued acting to lower wage ratios, the role of demand varies across countries.

We briefly present results where unskilled labor is the sum of low and medium education workers instead of efficiency units and where the unskilled wage is the simple average of the low and medium education wage. Table 3 does so showing the summary statistics for brevity. Compared to Table 2, the measured change in quantities is very similar, so the DTC effect is also very similar. However, Table 3 shows milder declines in wage ratios. For example, since the start of the sample, unweighted wages fell by 0.16% per year while those in Table 2 fell by 0.36% per year. As a result, both adjusted and unadjusted demand shifts were more favorable to skilled workers in Table 3. In particular, since the start of the sample, even adjusted demand shifts exceeded 0.2% per year, which could be enough to be considered to be skill biased. Yet the finding that shifting patterns in wage ratios over time are explained by shifts in demand and not supply continue to hold.

[22] For a given change in method/coverage, this is estimated simply as the change in ratio observed. Sometimes there are two surveys for the same year and sometimes the surveys cover different years. For multiple changes, these are added.

**Table 3: Contributions to Wage Ratios ($\sigma = 1.75$, high vs low and medium unweighted).**

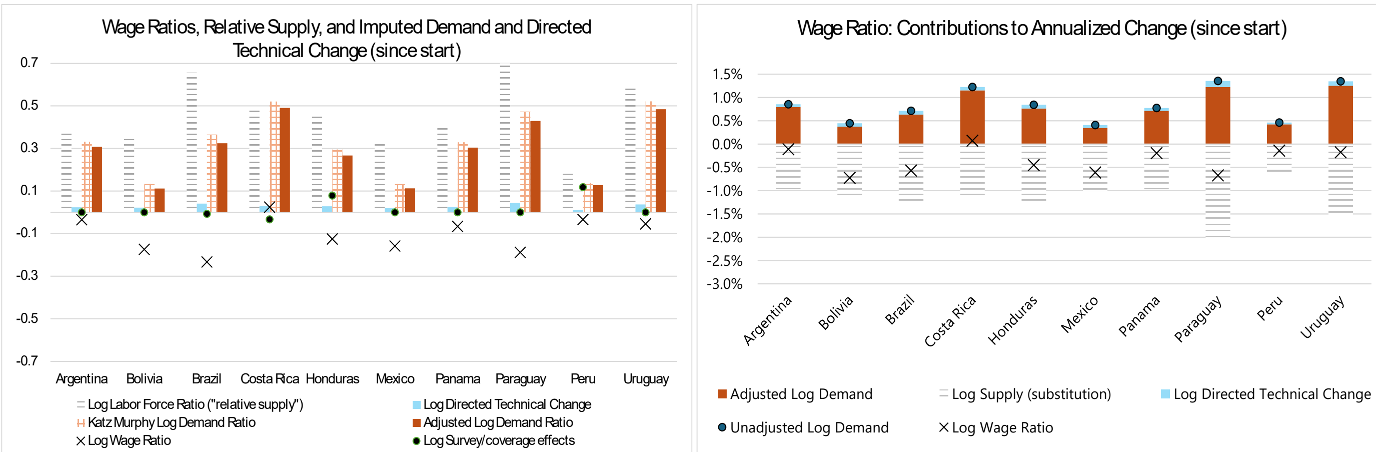
| | Year | Log Wage Ratio | Unadjusted Log Demand | Log Supply (substitution) | Log Directed Technical Change | Adjusted Log Demand |
|---|---|---|---|---|---|---|
| **Average** | | | | | | |
| *End-start (annualized)* | 30 | -0.16% | 0.68% | -0.84% | 0.47% | 0.21% |
| *2015-max (annualized)* | 16 | -0.86% | -0.24% | -0.62% | 0.35% | -0.59% |
| *End-2015 (annualized)* | 6 | -0.37% | 0.48% | -0.85% | 0.48% | 0.00% |
| **Median** | | | | | | |
| *End-start (annualized)* | 30 | -0.10% | 0.70% | -0.82% | 0.46% | 0.24% |
| *2015-max (annualized)* | 16 | -0.78% | 0.15% | -0.71% | 0.40% | -0.27% |
| *End-2015 (annualized)* | 7 | -0.15% | 0.43% | -0.83% | 0.46% | 0.11% |

**Lower elasticity (1.25)**

For $\sigma = 1.25$, analogues to Table 1 and 2 are in annex tables (A1 and A2) and Figure 3 illustrates developments since the start of the sample. In the left chart, an important methodological observation is that DTC is much lower than for $\sigma = 1.75$ as a share of the standard substitution effect and in absolute terms. (Recall that DTC would be zero for $\sigma = 1$.) As a result, the adjustment to demand in this figure is much smaller than for the higher elasticity such that even adjusted demand was skill biased for almost all countries (and still positive but broadly neutral in the rest). In the right chart, and unlike for the higher elasticity, adjusted demand not only increases the wage ratio but in all cases makes a larger contribution to the increase than DTC.

As reported in annex Table A1, average traditional demand became 32% more skill biased since the start of the sample (only slightly higher than the 27% for the higher elasticity), but average adjusted demand became 30% more skill biased (compared to broadly neutral change for the higher elasticity). DTC (3%) with the lower elasticity is a small fraction of that estimated for the higher elasticity. The smaller effect of a lower elasticity on the adjustment to demand is also visible over different time periods. For example, in the max-to-2015 period, both adjusted and unadjusted demand are broadly skill neutral on aggregate. However, the direction of skill bias in adjusted demand varies across countries. Table A2 reenforces such findings by decomposing annual wage ratio changes. Moreover, the lower average annual DTC effect (less than 0.1% per year) implies that, in a no-DTC counterfactual, the pace of wage ratio decrease would not have been much different. The illustration with a lower elasticity value underscores the importance of the elasticity parameter for ascertaining DTC effects and more generally for the DD-SS framework.

**Figure 3: Wage drivers and decomposition analysis ($\sigma = 1.25$, high vs low and medium).**




### Baseline elasticity with disaggregated unskilled labor

Returning to $\sigma = 1.75$, Tables A3 and A4 in the annex present results for high vs medium education workers. The high/medium wage ratio is at the same level as at the start of the sample. Part of the explanation for the absence of a decrease is that the supply of high education workers has grown only slightly faster than the supply of medium education workers. For example, the average supply ratio grew by 13% on average. Another implication of slow relative supply growth is that any DTC adjustment is modest. The net skill bias of adjusted demand is neutral (and just about positive unadjusted). However, when explaining developments during max-to-2015, decreases in the wage ratio are explained by demand shifts that were unskilled-biased.

Annex tables A5 and A6 present results for high vs low education workers. The high/low wage ratio fell by more than the medium/low ratio. Part of the difference in wage performance is that the ratio of high/low skilled workers grew rapidly, generating substantial downward pressure on the wage ratio via the substitution effect. Under the traditional framework, the wage ratio did not fall by even more due to substantial skill-biased shifts in unadjusted labor demand. By our framework, the explanation is that more than half of the substitution effect was offset by the DTC effect. When adjusted for DTC, demand shifts are broadly skill neutral. When explaining wage ratio decreases during the max-to-2015 period, unadjusted demand shifts were mixed but adjusted demand shifts were more consistently unskilled biased.

Comparisons of annex tables and of the left and right charts of Figure 4 show that the forces and counter forces are larger for the high/low ratios than for the high/med ratios and contribute more to the main results with aggregated unskilled labor. The findings that DTC lead to adjusted demand that was skill neutral over the length of the sample and since 2015 and unskilled-biased during max-to-2015 is common to both disaggregated ratios.

**Figure 4: Wage decomposition analysis ($\sigma = 1.75$, disaggregated unskilled labor, since sample start).**


These findings are also consistent when comparing across Figure 4 charts for individual countries. The forces and counter forces are larger for the high/low ratio than the high/medium ratio and the sign for adjusted demand is common. Interesting exceptions are Mexico and Peru, where there are no discernible rises in the ratio of high/medium supply. As a result, the modest changes in the high/medium ratio are due to traditional demand. Because there is no relative supply increase, there is no DTC effect, and no adjustment to demand. In contrast, there are material increases in those two countries' high/low supply ratios, important DTC effects, and skill-biased unadjusted demand effects that become skill-neutral when adjusted.

**Synthesis of results**

When explaining the decline in the skilled wage premium, supply increases through the substitution effect are consistent and important contributors. But supply's role is reduced when considering the DTC that supply increases induce. Accounting for DTC leads to qualitative changes in the role of demand with our baseline elasticity. Specifically, DTC makes the adjusted demand developments more favorable to unskilled workers. With the aid of Table 4, we recapitulate demand effects, recalling that this is a broadly defined residual that includes institutional factors.

**Table 4: Summary table for skill bias of demand shifts.**

| | 1.75 (high vs medium and low) | 1.75 (high vs medium) | 1.75 (high vs low) | 1.25 (high vs medium and low) |
|---|---|---|---|---|
| Since start | +,~ | +,~ | +,~ | +,+ |
| Max-to-2015 | ~,- | -,- | ~,- | ~,~ |
| Since 2015 | +,~ | +,~ | +,~ | +,+ |

+ indicates skill-biased, ~ indicates broadly neutral, - indicates unskill-biased. First entry is for unadjusted demand. Second entry is adjusted demand.

For $\sigma = 1.75$, demand changes that are calculated to be skill biased using the traditional method since the start of the sample and in the subset since 2015 become skill neutral in our adjusted approach. This result is robust to disaggregation of the unskilled group. Recall that $\sigma = 2$ would attribute all of the decline in the skill premium to unskill-biased adjusted demand shifts. However, when $\sigma = 1.25$, the DTC effect and resulting adjustment are not big enough to modify the unadjusted conclusion that demand developments were skill biased. Recall that $\sigma = 1$ would have no adjustment at all. In the max-to-2015 period, which is when wage premia fell faster, traditional demand changes were skill neutral and, for $\sigma = 1.75$, adjusted demand changes were unskilled biased. In general, the robustness tests tend to produce slightly more skill-biased demand shifts than the baseline results, but the broad patterns hold. Moreover, regardless of the elasticity or aggregation, it continues to be the case that changes in the speed of wage ratio decline imply changes in the skill bias of demand changes.

# 5. Conclusion and possible extensions

Using updated harmonized data for Latin America, this paper documents a continued decrease in the wage premium for highly-educated (post-secondary) workers. Since 2015, the pace of decrease has been in line with the long-run trend but notably slower than the period between when premia peaked and 2015. To interpret developments, we modify the demand-supply framework to account for directed technical change. In this framework, increases in the relative supply of more skilled workers induce skill-biased technical change, which tends to increase the wage premium and act against the traditional substitution effect. For a given change in the wage premium, DTC adjusts estimated demand shifts to make them less favorable to skilled workers.

With this framework, observed increases in the relative supply of more educated workers continue to consistently reduce the premium enjoyed by such workers. But observed changes in the speed of the wage premium decline are mainly explained by changes in the skill bias of demand. For example, under traditional demand, while the max-to-2015 period was skill neutral, demand shifts have since become skill biased (in line with the long-run trend). When we adjust demand for supply-induced DTC, which is material using our baseline elasticity of substitution, max-to-2015 shifts favored unskilled workers but have since returned to long-run skill neutral change.

Having used data for Latin America to introduce our modification to the demand-supply framework, the analysis could be extended to other regions or enriched within the region. Our preferred elasticity of substitution value of 1.75 for this data has significant implications for the role of demand in this application. Using a lower $\sigma = 1.25$, DTC and thus adjustments to demand are less material. This underscores the sensitivity to the parameter of even qualitative conclusions on DTC effects and for the DD-SS framework more broadly. Future work within the region could be finetuned by using country-specific estimates where data is adequate for estimation, while studies elsewhere should choose estimates carefully or seek new estimates.

Under the DTC framework, studies that might have been discarded[23] due to positive regression coefficients (which are inconsistent with traditional theory but can be rationalized in this framework) or too close to zero (which imply implausibly high elasticities under the traditional framework but values of close to 2 here) may warrant revival and application in the modified demand-supply framework.

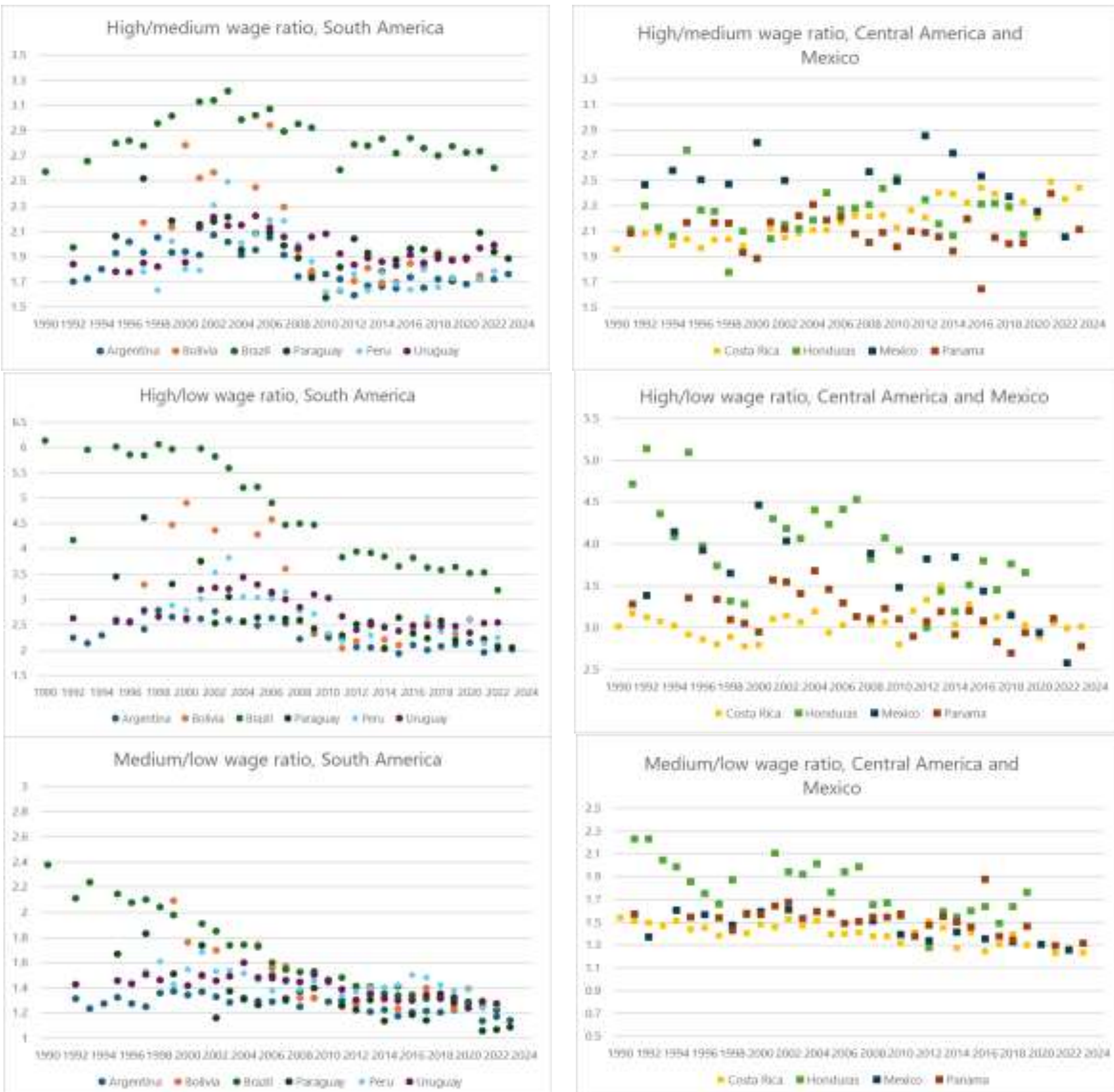
[23] See Havranek et al (2024) for an in-depth analysis of publication bias in studies of the elasticity of substitution and Behar (2025) for discussion of how these and econometric concerns are mitigated by the directed technical change framework.

Our proposed methodological change can be complemented by richer aggregation methods that account for other worker characteristics and possibly imperfect substitution between them. For example, demographic shifts linked to experience (FM) and female labor force participation (Manacorda et. al., 2010) are important, and technologies may be endogenous to them. The interplay between DTC, labor market institutions, and/or firm heterogeneity merits further analysis. It's also important to acknowledge that most of the decline in the variance of wages took place within education (and age and gender) groups and not between them (MS).

Our work to estimate supply-driven technical change is only half the task as isolating a technology component of demand shifts remains elusive. Isolation could be explored through unobserved global common factors that reflect global technology shifts (in turn possibly generated by skill supply shifts in major technology producers using our framework). Country-specific observable, albeit imperfect, demand proxies include technology-rich imports or investment, though isolating the *bias* rather than the quantity of technical change is an important challenge. An updated examination of other potential demand drivers including observable sectoral shifts and how those have varied over time could be analyzed as possible explanations for demand dynamics, including during the recent slowdown in the decline of the wage premium.

# Annex I. Wage ratio developments at disaggregated education levels

Broad dynamics observed for the ratio of high- to combined medium- and low-educated workers are also observed for high/medium and high/low wage ratios. For example, South America's hump shape and more recent relative flattening is apparent for both ratios. However, South America's high/medium ratio exhibits more of a flat S shape including some recent increases in the high/medium premium. For Central America and Mexico, high/low premia rose by less / fell by more than high/medium premia since the start of the time series, but the picture is mixed for developments since 2015. The medium/low ratio has also generally declined since 2015 and over longer horizons, which suggests rises in wages for those with low education levels continue to be important contributors to decreases in wage inequality.



# Annex 2. Wage ratio drivers and decomposition: lower elasticity

**Table A1: Wages, supply, demand, and directed technical change ($\sigma = 1.25$, high vs low and medium).**

| | Year | Wage Ratio | Log Wage Ratio | Labor Force Ratio | Log Labor Force Ratio ("relative supply") | Katz Murphy Log Demand Ratio | Log Directed Technical Change | Adjusted Log Demand Ratio |
|---|---|---|---|---|---|---|---|---|
| **Argentina** | | | | | | | | |
| Data start | 1992 | 1.98 | 0.30 | 0.19 | -0.72 | -0.35 | -0.04 | -0.30 |
| Ratio/year max | 1998 | 2.44 | 0.39 | 0.22 | -0.66 | -0.18 | -0.04 | -0.14 |
| 2015 | 2016-II | 1.86 | 0.27 | 0.39 | -0.41 | -0.07 | -0.03 | -0.05 |
| Data end | 2023-I | 1.83 | 0.26 | 0.45 | -0.34 | -0.02 | -0.02 | 0.01 |
| *End-start* | *31* | *-0.15* | *-0.03* | *0.26* | *0.37* | *0.33* | *0.02* | *0.31* |
| *2015-max* | *18* | *-0.58* | *-0.12* | *0.17* | *0.25* | *0.10* | *0.02* | *0.09* |
| *End-2015* | *7* | *-0.03* | *-0.01* | *0.06* | *0.07* | *0.06* | *0.00* | *0.05* |
| **Bolivia** | | | | | | | | |
| Data start | 1997 | 2.92 | 0.47 | 0.17 | -0.78 | -0.20 | -0.05 | -0.15 |
| Ratio/year max | 2000 | 4.02 | 0.60 | 0.17 | -0.78 | -0.02 | -0.05 | 0.03 |
| 2015 | 2015 | 1.91 | 0.28 | 0.28 | -0.56 | -0.21 | -0.03 | -0.17 |
| Data end | 2021 | 1.95 | 0.29 | 0.37 | -0.43 | -0.07 | -0.03 | -0.04 |
| *End-start* | *24* | *-0.96* | *-0.17* | *0.21* | *0.35* | *0.13* | *0.02* | *0.11* |
| *2015-max* | *15* | *-2.11* | *-0.32* | *0.11* | *0.22* | *-0.19* | *0.01* | *-0.20* |
| *End-2015* | *6* | *0.05* | *0.01* | *0.10* | *0.13* | *0.14* | *0.01* | *0.13* |
| **Brazil** | | | | | | | | |
| Data start | 1981 | 4.86 | 0.69 | 0.05 | -1.27 | -0.41 | -0.08 | -0.33 |
| Ratio/year max | 1982 | 5.66 | 0.75 | 0.05 | -1.33 | -0.38 | -0.08 | -0.30 |
| 2015 | 2015 | 3.63 | 0.56 | 0.16 | -0.79 | -0.09 | -0.05 | -0.04 |
| Data end | 2022 | 2.84 | 0.45 | 0.24 | -0.62 | -0.05 | -0.04 | -0.01 |
| *End-start* | *41* | *-2.02* | *-0.23* | *0.19* | *0.66* | *0.37* | *0.04* | *0.32* |
| *2015-max* | *33* | *-2.02* | *-0.19* | *0.12* | *0.54* | *0.30* | *0.03* | *0.26* |
| *End-2015* | *7* | *-0.79* | *-0.11* | *0.08* | *0.17* | *0.04* | *0.01* | *0.03* |
| **Costa Rica** | | | | | | | | |
| Data start | 1989 | 2.59 | 0.41 | 0.08 | -1.07 | -0.55 | -0.07 | -0.49 |
| Ratio/year max | 2013 | 2.97 | 0.47 | 0.21 | -0.67 | -0.08 | -0.04 | -0.04 |
| 2015 | 2015 | 2.86 | 0.46 | 0.21 | -0.68 | -0.11 | -0.04 | -0.07 |
| Data end | 2023 | 2.74 | 0.44 | 0.26 | -0.58 | -0.03 | -0.04 | 0.00 |
| *End-start* | *34* | *0.15* | *0.02* | *0.18* | *0.49* | *0.52* | *0.03* | *0.49* |
| *2015-max* | *2* | *-0.11* | *-0.02* | *0.00* | *-0.01* | *-0.03* | *0.00* | *-0.03* |
| *End-2015* | *8* | *-0.12* | *-0.02* | *0.05* | *0.10* | *0.08* | *0.01* | *0.07* |
| **Honduras** | | | | | | | | |
| Data start | 1991 | 4.02 | 0.60 | 0.03 | -1.49 | -0.73 | -0.09 | -0.64 |
| Ratio/year max | 1995 | 4.49 | 0.65 | 0.03 | -1.48 | -0.66 | -0.09 | -0.57 |
| 2015 | 2015 | 3.08 | 0.49 | 0.07 | -1.13 | -0.52 | -0.07 | -0.45 |
| Data end | 2019 | 3.01 | 0.48 | 0.09 | -1.03 | -0.43 | -0.06 | -0.37 |
| *End-start* | *28* | *-1.01* | *-0.13* | *0.06* | *0.45* | *0.30* | *0.03* | *0.27* |
| *2015-max* | *20* | *-1.40* | *-0.16* | *0.04* | *0.34* | *0.14* | *0.02* | *0.12* |
| *End-2015* | *4* | *-0.07* | *-0.01* | *0.02* | *0.10* | *0.09* | *0.01* | *0.08* |
| **Mexico** | | | | | | | | |
| Data start | 1994 | 3.56 | 0.55 | 0.11 | -0.97 | -0.28 | -0.06 | -0.22 |
| Ratio/year max | 2000 | 3.67 | 0.56 | 0.14 | -0.87 | -0.16 | -0.05 | -0.11 |
| 2015 | 2016 | 2.85 | 0.46 | 0.20 | -0.71 | -0.14 | -0.04 | -0.10 |
| Data end | 2020 | 2.47 | 0.39 | 0.23 | -0.64 | -0.15 | -0.04 | -0.11 |
| *End-start* | *26* | *-1.09* | *-0.16* | *0.12* | *0.33* | *0.13* | *0.02* | *0.11* |
| *2015-max* | *16* | *-0.82* | *-0.11* | *0.06* | *0.16* | *0.02* | *0.01* | *0.01* |
| *End-2015* | *4* | *-0.38* | *-0.06* | *0.03* | *0.07* | *-0.01* | *0.00* | *-0.01* |
| **Panama** | | | | | | | | |
| Data start | 1989 | 2.70 | 0.43 | 0.13 | -0.88 | -0.34 | -0.06 | -0.29 |
| Ratio/year max | 2004 | 2.91 | 0.46 | 0.20 | -0.69 | -0.11 | -0.04 | -0.07 |
| 2015 | 2015 | 2.56 | 0.41 | 0.30 | -0.52 | -0.01 | -0.03 | 0.02 |
| Data end | 2023 | 2.32 | 0.37 | 0.34 | -0.47 | -0.01 | -0.03 | 0.02 |
| *End-start* | *34* | *-0.38* | *-0.07* | *0.21* | *0.41* | *0.33* | *0.03* | *0.30* |
| *2015-max* | *11* | *-0.35* | *-0.06* | *0.10* | *0.17* | *0.10* | *0.01* | *0.09* |
| *End-2015* | *8* | *-0.24* | *-0.04* | *0.04* | *0.05* | *0.00* | *0.00* | *-0.01* |
| **Paraguay** | | | | | | | | |
| Data start | 1995 | 3.04 | 0.48 | 0.07 | -1.14 | -0.53 | -0.07 | -0.46 |
| Ratio/year max | 1997 | 3.90 | 0.59 | 0.08 | -1.09 | -0.35 | -0.07 | -0.28 |
| 2015 | 2015 | 2.28 | 0.36 | 0.24 | -0.63 | -0.18 | -0.04 | -0.14 |
| Data end | 2023 | 1.97 | 0.29 | 0.37 | -0.43 | -0.06 | -0.03 | -0.03 |
| *End-start* | *28* | *-1.07* | *-0.19* | *0.30* | *0.71* | *0.47* | *0.04* | *0.43* |
| *2015-max* | *18* | *-1.63* | *-0.23* | *0.16* | *0.47* | *0.17* | *0.03* | *0.15* |
| *End-2015* | *8* | *-0.31* | *-0.06* | *0.13* | *0.20* | *0.12* | *0.01* | *0.11* |
| **Peru** | | | | | | | | |
| Data start | 1998 | 2.11 | 0.33 | 0.19 | -0.72 | -0.31 | -0.04 | -0.26 |
| Ratio/year max | 2003b | 3.11 | 0.49 | 0.22 | -0.66 | -0.04 | -0.04 | 0.00 |
| 2015 | 2015 | 1.96 | 0.29 | 0.27 | -0.57 | -0.21 | -0.04 | -0.17 |
| Data end | 2022 | 1.96 | 0.29 | 0.29 | -0.53 | -0.17 | -0.03 | -0.14 |
| *End-start* | *24* | *-0.16* | *-0.03* | *0.10* | *0.18* | *0.14* | *0.01* | *0.13* |
| *2015-max* | *12* | *-1.16* | *-0.20* | *0.05* | *0.08* | *-0.17* | *0.01* | *-0.17* |
| *End-2015* | *7* | *0.00* | *0.00* | *0.03* | *0.04* | *0.04* | *0.00* | *0.04* |
| **Uruguay** | | | | | | | | |
| Data start | 1989 | 2.33 | 0.37 | 0.06 | -1.19 | -0.73 | -0.07 | -0.66 |
| Ratio/year max | 2005 | 2.67 | 0.43 | 0.19 | -0.71 | -0.18 | -0.04 | -0.13 |
| 2015 | 2015 | 2.06 | 0.31 | 0.21 | -0.67 | -0.28 | -0.04 | -0.24 |
| Data end | 2020 | 2.06 | 0.31 | 0.25 | -0.60 | -0.21 | -0.04 | -0.17 |
| *End-start* | *31* | *-0.27* | *-0.05* | *0.19* | *0.59* | *0.52* | *0.04* | *0.48* |
| *2015-max* | *10* | *-0.61* | *-0.11* | *0.02* | *0.04* | *-0.10* | *0.00* | *-0.10* |
| *End-2015* | *5* | *0.00* | *0.00* | *0.04* | *0.07* | *0.07* | *0.00* | *0.06* |
| **Average** | | | | | | | | |
| *End-start* | 30 | -0.70 | -0.10 | 0.18 | 0.45 | 0.32 | 0.03 | 0.30 |
| *2015-max* | 16 | -1.08 | -0.15 | 0.08 | 0.23 | 0.04 | 0.01 | 0.02 |
| *End-2015* | 6 | -0.19 | -0.03 | 0.06 | 0.10 | 0.06 | 0.01 | 0.06 |
| **Median** | | | | | | | | |
| *End-start* | 30 | -0.67 | -0.10 | 0.19 | 0.43 | 0.33 | 0.03 | 0.31 |
| *End-max* | 16 | -0.99 | -0.14 | 0.08 | 0.19 | 0.06 | 0.01 | 0.05 |
| *End-2015* | *7* | *-0.10* | *-0.01* | *0.05* | *0.09* | *0.06* | *0.01* | *0.06* |

**Table A2: Contributions to Wage Ratios ($\sigma = 1.25$, high vs low and medium).**

| | Year | Log Wage Ratio | Unadjusted Log Demand | Log Supply (substitution) | Log Directed Technical Change | Adjusted Log Demand |
|---|---|---|---|---|---|---|
| **Argentina** | | | | | | |
| Data start | 1992 | 0.30 | -0.28 | 0.57 | -0.04 | -0.24 |
| Ratio/year max | 1998 | 0.39 | -0.14 | 0.53 | -0.03 | -0.11 |
| 2015 | 2016-II | 0.27 | -0.06 | 0.33 | -0.02 | -0.04 |
| Data end | 2023-I | 0.26 | -0.01 | 0.27 | -0.02 | 0.00 |
| *End-start (annualized)* | 31 | -0.1% | *0.9%* | *-1.0%* | *0.1%* | *0.8%* |
| *2015-max (annualized)* | 18 | -0.7% | *0.5%* | *-1.1%* | *0.1%* | *0.4%* |
| *End-2015 (annualized)* | 7 | -0.1% | *0.7%* | *-0.8%* | *0.0%* | *0.6%* |
| **Bolivia** | | | | | | |
| Data start | 1997 | 0.47 | -0.16 | 0.62 | -0.04 | -0.12 |
| Ratio/year max | 2000 | 0.60 | -0.02 | 0.62 | -0.04 | 0.02 |
| 2015 | 2015 | 0.28 | -0.17 | 0.45 | -0.03 | -0.14 |
| Data end | 2021 | 0.29 | -0.05 | 0.34 | -0.02 | -0.03 |
| *End-start (annualized)* | 24 | -0.7% | *0.4%* | *-1.2%* | *0.1%* | *0.4%* |
| *2015-max (annualized)* | 15 | -2.2% | *-1.0%* | *-1.2%* | *0.1%* | *-1.1%* |
| *End-2015* | 6 | 0.2% | *1.9%* | *-1.7%* | *0.1%* | *1.8%* |
| **Brazil** | | | | | | |
| Data start | 1981 | 0.69 | -0.33 | 1.02 | -0.06 | -0.27 |
| Ratio/year max | 1982 | 0.75 | -0.31 | 1.06 | -0.07 | -0.24 |
| 2015 | 2015 | 0.56 | -0.07 | 0.63 | -0.04 | -0.03 |
| Data end | 2022 | 0.45 | -0.04 | 0.49 | -0.03 | -0.01 |
| *End-start (annualized)* | 41 | -0.6% | *0.7%* | *-1.3%* | *0.1%* | *0.6%* |
| *2015-max (annualized)* | 33 | -0.6% | *0.7%* | *-1.3%* | *0.1%* | *0.6%* |
| *End-2015 (annualized)* | 7 | -1.5% | *0.4%* | *-2.0%* | *0.1%* | *0.3%* |
| **Costa Rica** | | | | | | |
| Data start | 1989 | 0.41 | -0.44 | 0.86 | -0.05 | -0.39 |
| Ratio/year max | 2013 | 0.47 | -0.07 | 0.54 | -0.03 | -0.03 |
| 2015 | 2015 | 0.46 | -0.09 | 0.54 | -0.03 | -0.05 |
| Data end | 2023 | 0.44 | -0.03 | 0.46 | -0.03 | 0.00 |
| *End-start (annualized)* | 34 | 0.1% | *1.2%* | *-1.2%* | *0.1%* | *1.2%* |
| *2015-max (annualized)* | 2 | -0.8% | *-1.0%* | *0.2%* | *0.0%* | *-1.0%* |
| *End-2015 (annualized)* | 8 | -0.2% | *0.8%* | *-1.0%* | *0.1%* | *0.7%* |
| **Honduras** | | | | | | |
| Data start | 1991 | 0.60 | -0.58 | 1.19 | -0.07 | -0.51 |
| Ratio/year max | 1995 | 0.65 | -0.53 | 1.18 | -0.07 | -0.46 |
| 2015 | 2015 | 0.49 | -0.42 | 0.91 | -0.06 | -0.36 |
| Data end | 2019 | 0.48 | -0.35 | 0.83 | -0.05 | -0.30 |
| *End-start (annualized)* | 28 | -0.4% | *0.8%* | *-1.3%* | *0.1%* | *0.8%* |
| *2015-max (annualized)* | 20 | -0.8% | *0.6%* | *-1.4%* | *0.1%* | *0.5%* |
| *End-2015 (annualized)* | 4 | -0.3% | *1.8%* | *-2.0%* | *0.1%* | *1.7%* |
| **Mexico** | | | | | | |
| Data start | 1994 | 0.55 | -0.22 | 0.77 | -0.05 | -0.18 |
| Ratio/year max | 2000 | 0.56 | -0.13 | 0.69 | -0.04 | -0.08 |
| 2015 | 2016 | 0.46 | -0.11 | 0.57 | -0.04 | -0.08 |
| Data end | 2020 | 0.39 | -0.12 | 0.51 | -0.03 | -0.09 |
| *End-start (annualized)* | 26 | -0.6% | *0.4%* | *-1.0%* | *0.1%* | *0.3%* |
| *2015-max (annualized)* | 16 | -0.7% | *0.1%* | *-0.8%* | *0.0%* | *0.1%* |
| *End-2015 (annualized)* | 4 | -1.6% | *-0.1%* | *-1.4%* | *0.1%* | *-0.2%* |
| **Panama** | | | | | | |
| Data start | 1989 | 0.43 | -0.27 | 0.71 | -0.04 | -0.23 |
| Ratio/year max | 2004 | 0.46 | -0.09 | 0.55 | -0.03 | -0.06 |
| 2015 | 2015 | 0.41 | -0.01 | 0.42 | -0.03 | 0.02 |
| Data end | 2023 | 0.37 | -0.01 | 0.38 | -0.02 | 0.01 |
| *End-start (annualized)* | 34 | -0.2% | *0.8%* | *-1.0%* | *0.1%* | *0.7%* |
| *2015-max (annualized)* | 11 | -0.5% | *0.7%* | *-1.2%* | *0.1%* | *0.7%* |
| *End-2015 (annualized)* | 8 | -0.5% | *0.0%* | *-0.5%* | *0.0%* | *-0.1%* |
| **Paraguay** | | | | | | |
| Data start | 1995 | 0.48 | -0.43 | 0.91 | -0.06 | -0.37 |
| Ratio/year max | 1997 | 0.59 | -0.28 | 0.87 | -0.05 | -0.23 |
| 2015 | 2015 | 0.36 | -0.14 | 0.50 | -0.03 | -0.11 |
| Data end | 2023 | 0.29 | -0.05 | 0.34 | -0.02 | -0.03 |
| *End-start (annualized)* | 28 | -0.7% | *1.4%* | *-2.0%* | *0.1%* | *1.2%* |
| *2015-max (annualized)* | 18 | -1.3% | *0.8%* | *-2.1%* | *0.1%* | *0.6%* |
| *End-2015 (annualized)* | 8 | -0.8% | *1.2%* | *-2.0%* | *0.1%* | *1.1%* |
| **Peru** | | | | | | |
| Data start | 1998 | 0.33 | -0.25 | 0.57 | -0.04 | -0.21 |
| Ratio/year max | 2003b | 0.49 | -0.03 | 0.53 | -0.03 | 0.00 |
| 2015 | 2015 | 0.29 | -0.17 | 0.46 | -0.03 | -0.14 |
| Data end | 2022 | 0.29 | -0.14 | 0.43 | -0.03 | -0.11 |
| *End-start (annualized)* | 24 | -0.1% | *0.5%* | *-0.6%* | *0.0%* | *0.4%* |
| *2015-max (annualized)* | 12 | -1.7% | *-1.1%* | *-0.6%* | *0.0%* | *-1.2%* |
| *End-2015 (annualized)* | 7 | 0.0% | *0.5%* | *-0.5%* | *0.0%* | *0.4%* |
| **Uruguay** | | | | | | |
| Data start | 1989 | 0.37 | -0.59 | 0.95 | -0.06 | -0.53 |
| Ratio/year max | 2005 | 0.43 | -0.14 | 0.57 | -0.04 | -0.11 |
| 2015 | 2015 | 0.31 | -0.22 | 0.54 | -0.03 | -0.19 |
| Data end | 2020 | 0.31 | -0.17 | 0.48 | -0.03 | -0.14 |
| *End-start (annualized)* | 31 | -0.2% | *1.3%* | *-1.5%* | *0.1%* | *1.3%* |
| *2015-max (annualized)* | 10 | -1.1% | *-0.8%* | *-0.3%* | *0.0%* | *-0.8%* |
| *End-2015 (annualized)* | 5 | 0.0% | *1.1%* | *-1.1%* | *0.1%* | *1.0%* |
| **Average** | | | | | | |
| *End-start (annualized)* | 30 | -0.36% | 0.84% | -1.20% | 0.08% | 0.77% |
| *2015.-max (annualized)* | 16 | -1.03% | -0.06% | -0.98% | 0.06% | -0.12% |
| *End-2015 (annualized)* | 6 | -0.48% | 0.81% | -1.29% | 0.08% | 0.73% |
| **Median** | | | | | | |
| *End-start (annualized)* | 30 | -0.32% | 0.81% | -1.16% | 0.07% | 0.74% |
| *2015.-max (annualized)* | 16 | -0.83% | 0.28% | -1.14% | 0.07% | 0.22% |
| *End-2015 (annualized)* | 7 | -0.24% | 0.71% | -1.25% | 0.08% | 0.65% |

# Annex 3. Wage ratio drivers and decomposition: disaggregated unskilled labor

**Table A3: Wages, supply, demand, and directed technical change ($\sigma = 1.75$, high vs medium).**

| | Year | Wage Ratio | Log Wage Ratio | Labor Force Ratio | Log Labor Force Ratio (relative supply) | Katz Murphy Log Demand Ratio | Log Directed Technical Change | Adjusted Log Demand Ratio |
|---|---|---|---|---|---|---|---|---|
| **Argentina** | | | | | | | | |
| Data start | 1992 | 1.70 | 0.23 | 0.52 | -0.29 | 0.12 | -0.16 | 0.28 |
| Ratio/year max | 1998 | 2.10 | 0.32 | 0.56 | -0.25 | 0.31 | -0.14 | 0.45 |
| 2015 | 2016-II | 1.74 | 0.24 | 0.71 | -0.15 | 0.27 | -0.08 | 0.36 |
| Data end | 2023-I | 1.76 | 0.25 | 0.71 | -0.15 | 0.28 | -0.08 | 0.37 |
| *End-start* | *31* | *0.06* | *0.01* | *0.19* | *0.14* | *0.16* | *0.08* | *0.09* |
| *2015-max* | *18* | *-0.36* | *-0.08* | *0.15* | *0.10* | *-0.04* | *0.06* | *-0.10* |
| *End-2015* | *7* | *0.02* | *0.01* | *0.00* | *0.00* | *0.01* | *0.00* | *0.01* |
| **Bolivia** | | | | | | | | |
| Data start | 1997 | 2.17 | 0.34 | 0.75 | -0.13 | 0.46 | -0.07 | 0.53 |
| Ratio/year max | 2006 | 2.94 | 0.47 | 0.78 | -0.11 | 0.71 | -0.06 | 0.77 |
| 2015 | 2015 | 1.70 | 0.23 | 0.71 | -0.15 | 0.26 | -0.08 | 0.34 |
| Data end | 2021 | 1.75 | 0.24 | 0.85 | -0.07 | 0.35 | -0.04 | 0.39 |
| *End-start* | *24* | *-0.42* | *-0.09* | *0.10* | *0.05* | *-0.11* | *0.03* | *-0.14* |
| *2015-max* | *9* | *-1.24* | *-0.24* | *-0.06* | *-0.04* | *-0.45* | *-0.02* | *-0.43* |
| *End-2015* | *6* | *0.05* | *0.01* | *0.13* | *0.07* | *0.10* | *0.04* | *0.06* |
| **Brazil** | | | | | | | | |
| Data start | 1981 | 2.28 | 0.36 | 0.61 | -0.22 | 0.41 | -0.12 | 0.53 |
| Ratio/year max | 2003 | 3.22 | 0.51 | 0.37 | -0.43 | 0.46 | -0.24 | 0.70 |
| 2015 | 2015 | 3.04 | 0.48 | 0.44 | -0.36 | 0.49 | -0.20 | 0.69 |
| Data end | 2022 | 2.61 | 0.42 | 0.50 | -0.30 | 0.43 | -0.17 | 0.60 |
| *End-start* | *41* | *0.33* | *0.06* | *-0.11* | *-0.08* | *0.02* | *-0.05* | *0.06* |
| *2015-max* | *12* | *-0.18* | *-0.02* | *0.07* | *0.07* | *0.03* | *0.04* | *-0.01* |
| *End-2015* | *7* | *-0.43* | *-0.07* | *0.06* | *0.06* | *-0.06* | *0.03* | *-0.09* |
| **Costa Rica** | | | | | | | | |
| Data start | 1989 | 1.91 | 0.28 | 0.40 | -0.40 | 0.09 | -0.23 | 0.31 |
| Ratio/year max | 2021 | 2.49 | 0.40 | 0.65 | -0.18 | 0.51 | -0.10 | 0.61 |
| 2015 | 2015 | 2.33 | 0.37 | 0.67 | -0.18 | 0.47 | -0.10 | 0.56 |
| Data end | 2023 | 2.44 | 0.39 | 0.67 | -0.17 | 0.50 | -0.10 | 0.60 |
| *End-start* | *34* | *0.54* | *0.11* | *0.27* | *0.23* | *0.42* | *0.13* | *0.29* |
| *2015-max* | *n/a* | *-0.17* | *-0.03* | *0.01* | *0.01* | *-0.04* | *0.01* | *-0.05* |
| *End-2015* | *8* | *0.12* | *0.02* | *0.00* | *0.00* | *0.04* | *0.00* | *0.04* |
| **Honduras** | | | | | | | | |
| Data start | 1991 | 2.11 | 0.32 | 0.27 | -0.56 | 0.00 | -0.32 | 0.32 |
| Ratio/year max | 1995 | 2.74 | 0.44 | 0.24 | -0.62 | 0.14 | -0.35 | 0.49 |
| 2015 | 2015 | 2.20 | 0.34 | 0.36 | -0.45 | 0.15 | -0.25 | 0.40 |
| Data end | 2019 | 2.08 | 0.32 | 0.40 | -0.40 | 0.16 | -0.23 | 0.38 |
| *End-start* | *28* | *-0.04* | *-0.01* | *0.13* | *0.16* | *0.15* | *0.09* | *0.06* |
| *2015-max* | *20* | *-0.54* | *-0.10* | *0.12* | *0.18* | *0.01* | *0.10* | *-0.09* |
| *End-2015* | *4* | *-0.12* | *-0.02* | *0.04* | *0.05* | *0.00* | *0.03* | *-0.02* |
| **Mexico** | | | | | | | | |
| Data start | 1994 | 2.58 | 0.41 | 0.46 | -0.34 | 0.38 | -0.19 | 0.57 |
| Ratio/year max | 2012 | 2.85 | 0.46 | 0.40 | -0.40 | 0.39 | -0.23 | 0.62 |
| 2015 | 2016 | 2.54 | 0.40 | 0.41 | -0.39 | 0.32 | -0.22 | 0.54 |
| Data end | 2020 | 2.26 | 0.35 | 0.44 | -0.36 | 0.26 | -0.20 | 0.46 |
| *End-start* | *26* | *-0.32* | *-0.06* | *-0.02* | *-0.02* | *-0.12* | *-0.01* | *-0.11* |
| *2015-max* | *4* | *-0.32* | *-0.05* | *0.01* | *0.01* | *-0.08* | *0.01* | *-0.08* |
| *End-2015* | *4* | *-0.28* | *-0.05* | *0.03* | *0.03* | *-0.06* | *0.02* | *-0.08* |
| **Panama** | | | | | | | | |
| Data start | 1989 | 2.03 | 0.31 | 0.45 | -0.35 | 0.19 | -0.20 | 0.39 |
| Ratio/year max | 2004 | 2.31 | 0.36 | 0.57 | -0.24 | 0.39 | -0.14 | 0.53 |
| 2015 | 2015 | 2.20 | 0.34 | 0.69 | -0.16 | 0.43 | -0.09 | 0.53 |
| Data end | 2023 | 2.11 | 0.32 | 0.64 | -0.19 | 0.38 | -0.11 | 0.48 |
| *End-start* | *34* | *0.08* | *0.02* | *0.19* | *0.16* | *0.19* | *0.09* | *0.10* |
| *2015-max* | *11* | *-0.11* | *-0.02* | *0.11* | *0.08* | *0.04* | *0.04* | *0.00* |
| *End-2015* | *8* | *-0.08* | *-0.02* | *-0.04* | *-0.03* | *-0.06* | *-0.02* | *-0.04* |
| **Paraguay** | | | | | | | | |
| Data start | 1995 | 2.07 | 0.31 | 0.41 | -0.39 | 0.16 | -0.22 | 0.38 |
| Ratio/year max | 1997 | 2.52 | 0.40 | 0.43 | -0.36 | 0.34 | -0.20 | 0.55 |
| 2015 | 2015 | 1.88 | 0.27 | 0.69 | -0.16 | 0.32 | -0.09 | 0.41 |
| Data end | 2023 | 1.89 | 0.28 | 0.80 | -0.10 | 0.39 | -0.05 | 0.44 |
| *End-start* | *28* | *-0.18* | *-0.04* | *0.39* | *0.29* | *0.22* | *0.16* | *0.06* |
| *2015-max* | *18* | *-0.64* | *-0.13* | *0.26* | *0.20* | *-0.02* | *0.11* | *-0.14* |
| *End-2015* | *8* | *0.01* | *0.00* | *0.11* | *0.06* | *0.07* | *0.04* | *0.03* |
| **Peru** | | | | | | | | |
| Data start | 1998 | 1.64 | 0.21 | 0.60 | -0.23 | 0.15 | -0.13 | 0.28 |
| Ratio/year max | 2003b | 2.49 | 0.40 | 0.63 | -0.20 | 0.49 | -0.11 | 0.61 |
| 2015 | 2015 | 1.68 | 0.23 | 0.61 | -0.21 | 0.18 | -0.12 | 0.30 |
| Data end | 2022 | 1.79 | 0.25 | 0.58 | -0.24 | 0.21 | -0.13 | 0.34 |
| *End-start* | *24* | *0.15* | *0.04* | *-0.01* | *-0.01* | *0.06* | *-0.01* | *0.06* |
| *2015-max* | *12* | *-0.81* | *-0.17* | *-0.02* | *-0.01* | *-0.31* | *-0.01* | *-0.30* |
| *End-2015* | *7* | *0.10* | *0.03* | *-0.03* | *-0.02* | *0.02* | *-0.01* | *0.04* |
| **Uruguay** | | | | | | | | |
| Data start | 1989 | 1.85 | 0.27 | 0.22 | -0.66 | -0.19 | -0.37 | 0.18 |
| Ratio/year max | 2005 | 2.22 | 0.35 | 0.49 | -0.31 | 0.30 | -0.17 | 0.47 |
| 2015 | 2015 | 1.83 | 0.26 | 0.48 | -0.32 | 0.14 | -0.18 | 0.32 |
| Data end | 2020 | 1.89 | 0.28 | 0.49 | -0.31 | 0.18 | -0.17 | 0.35 |
| *End-start* | *31* | *0.04* | *0.01* | *0.27* | *0.35* | *0.37* | *0.20* | *0.17* |
| *2015-max* | *10* | *-0.39* | *-0.08* | *-0.02* | *-0.01* | *-0.16* | *-0.01* | *-0.15* |
| *End-2015* | *5* | *0.06* | *0.01* | *0.02* | *0.02* | *0.04* | *0.01* | *0.03* |
| **Average** | | | | | | | | |
| *End-start* | 30 | 0.02 | 0.00 | 0.14 | 0.13 | 0.13 | 0.07 | 0.06 |
| *2015-max* | 13 | -0.48 | -0.09 | 0.06 | 0.06 | -0.10 | 0.03 | -0.14 |
| *End-2015* | 6 | -0.06 | -0.01 | 0.03 | 0.02 | 0.01 | 0.01 | 0.00 |
| **Median** | | | | | | | | |
| *End-start* | 30 | 0.05 | 0.01 | 0.16 | 0.15 | 0.16 | 0.08 | 0.06 |
| *2015-max* | 12 | -0.38 | -0.08 | 0.04 | 0.04 | -0.04 | 0.02 | -0.09 |
| *End-2015* | *7* | *0.02* | *0.00* | *0.02* | *0.02* | *0.02* | *0.01* | *0.02* |

### Table A4: Contributions to Wage Ratios ($\sigma = 1.75$, high vs medium).

| | Year | Log Wage Ratio | Unadjusted Log Demand | Log Supply (substitution) | Log Directed Technical Change | Adjusted Log Demand |
|---|---|---|---|---|---|---|
| **Argentina** | | | | | | |
| Data start | 1992 | 0.23 | 0.07 | 0.16 | -0.09 | 0.16 |
| Ratio/year max | 1998 | 0.32 | 0.18 | 0.14 | -0.08 | 0.26 |
| 2015 | 2016-II | 0.24 | 0.16 | 0.09 | -0.05 | 0.20 |
| Data end | 2023-I | 0.25 | 0.16 | 0.08 | -0.05 | 0.21 |
| *End-start (annualized)* | 31 | 0.0% | *0.3%* | *-0.3%* | *0.1%* | *0.2%* |
| *2015-max (annualized)* | 18 | -0.5% | *-0.1%* | *-0.3%* | *0.2%* | *-0.3%* |
| *End-2015 (annualized)* | 7 | 0.1% | *0.1%* | *0.0%* | *0.0%* | *0.1%* |
| **Bolivia** | | | | | | |
| Data start | 1997 | 0.34 | 0.26 | 0.07 | -0.04 | 0.31 |
| Ratio/year max | 2006 | 0.47 | 0.41 | 0.06 | -0.04 | 0.44 |
| 2015 | 2015 | 0.23 | 0.15 | 0.08 | -0.05 | 0.19 |
| Data end | 2021 | 0.24 | 0.20 | 0.04 | -0.02 | 0.23 |
| *End-start (annualized)* | 24 | -0.4% | *-0.3%* | *-0.1%* | *0.1%* | *-0.3%* |
| *2015-max (annualized)* | 9 | -2.7% | *-2.9%* | *0.2%* | *-0.1%* | *-2.8%* |
| *End-2015 (annualized)* | 6 | 0.2% | *0.9%* | *-0.7%* | *0.4%* | *0.5%* |
| **Brazil** | | | | | | |
| Data start | 1981 | 0.36 | 0.23 | 0.12 | -0.07 | 0.30 |
| Ratio/year max | 2003 | 0.51 | 0.26 | 0.25 | -0.14 | 0.40 |
| 2015 | 2015 | 0.48 | 0.28 | 0.21 | -0.12 | 0.39 |
| Data end | 2022 | 0.42 | 0.24 | 0.17 | -0.10 | 0.34 |
| *End-start (annualized)* | 41 | 0.1% | *0.0%* | *0.1%* | *-0.1%* | *0.1%* |
| *2015-max (annualized)* | 12 | -0.2% | *0.1%* | *-0.3%* | *0.2%* | *-0.1%* |
| *End-2015 (annualized)* | 7 | -1.0% | *-0.5%* | *-0.5%* | *0.3%* | *-0.7%* |
| **Costa Rica** | | | | | | |
| Data start | 1989 | 0.28 | 0.05 | 0.23 | -0.13 | 0.18 |
| Ratio/year max | 2021 | 0.40 | 0.29 | 0.11 | -0.06 | 0.35 |
| 2015 | 2015 | 0.37 | 0.27 | 0.10 | -0.06 | 0.32 |
| Data end | 2023 | 0.39 | 0.29 | 0.10 | -0.06 | 0.34 |
| *End-start (annualized)* | 34 | 0.3% | *0.7%* | *-0.4%* | *0.2%* | *0.5%* |
| *2015-max (annualized)* | n/a | n/a | n/a | n/a | n/a | n/a |
| *End-2015 (annualized)* | 8 | 0.3% | *0.3%* | *0.0%* | *0.0%* | *0.3%* |
| **Honduras** | | | | | | |
| Data start | 1991 | 0.32 | 0.00 | 0.32 | -0.18 | 0.18 |
| Ratio/year max | 1995 | 0.44 | 0.08 | 0.36 | -0.20 | 0.28 |
| 2015 | 2015 | 0.34 | 0.09 | 0.26 | -0.14 | 0.23 |
| Data end | 2019 | 0.32 | 0.09 | 0.23 | -0.13 | 0.22 |
| *End-start (annualized)* | 28 | 0.0% | *0.3%* | *-0.3%* | *0.2%* | *0.1%* |
| *2015-max (annualized)* | 20 | -0.5% | *0.0%* | *-0.5%* | *0.3%* | *-0.3%* |
| *End-2015 (annualized)* | 4 | -0.6% | *0.1%* | *-0.7%* | *0.4%* | *-0.3%* |
| **Mexico** | | | | | | |
| Data start | 1994 | 0.41 | 0.219 | 0.19 | -0.11 | 0.33 |
| Ratio/year max | 2012 | 0.46 | 0.22 | 0.23 | -0.13 | 0.35 |
| 2015 | 2016 | 0.40 | 0.18 | 0.22 | -0.13 | 0.31 |
| Data end | 2020 | 0.35 | 0.148 | 0.21 | -0.12 | 0.26 |
| *End-start (annualized)* | 26 | -0.2% | *-0.3%* | *0.0%* | *0.0%* | *-0.2%* |
| *2015-max (annualized)* | 4 | -1.3% | *-1.1%* | *-0.2%* | *0.1%* | *-1.2%* |
| *End-2015 (annualized)* | 4 | -1.3% | *-0.8%* | *-0.4%* | *0.2%* | *-1.1%* |
| **Panama** | | | | | | |
| Data start | 1989 | 0.31 | 0.109 | 0.20 | -0.11 | 0.22 |
| Ratio/year max | 2004 | 0.36 | 0.23 | 0.14 | -0.08 | 0.30 |
| 2015 | 2015 | 0.34 | 0.25 | 0.09 | -0.05 | 0.30 |
| Data end | 2023 | 0.32 | 0.215 | 0.11 | -0.06 | 0.28 |
| *End-start (annualized)* | 34 | 0.1% | *0.3%* | *-0.3%* | *0.1%* | *0.2%* |
| *2015-max (annualized)* | 11 | -0.2% | *0.2%* | *-0.4%* | *0.2%* | *0.0%* |
| *End-2015 (annualized)* | 8 | -0.2% | *-0.4%* | *0.2%* | *-0.1%* | *-0.3%* |
| **Paraguay** | | | | | | |
| Data start | 1995 | 0.31 | 0.094 | 0.22 | -0.12 | 0.22 |
| Ratio/year max | 1997 | 0.40 | 0.20 | 0.21 | -0.12 | 0.31 |
| 2015 | 2015 | 0.27 | 0.18 | 0.09 | -0.05 | 0.23 |
| Data end | 2023 | 0.28 | 0.221 | 0.05 | -0.03 | 0.25 |
| *End-start (annualized)* | 28 | -0.1% | *0.5%* | *-0.6%* | *0.3%* | *0.1%* |
| *2015-max (annualized)* | 18 | -0.7% | *-0.1%* | *-0.6%* | *0.4%* | *-0.4%* |
| *End-2015 (annualized)* | 8 | 0.0% | *0.5%* | *-0.5%* | *0.3%* | *0.2%* |
| **Peru** | | | | | | |
| Data start | 1998 | 0.21 | 0.085 | 0.13 | -0.07 | 0.16 |
| Ratio/year max | 2003b | 0.40 | 0.28 | 0.11 | -0.06 | 0.35 |
| 2015 | 2015 | 0.23 | 0.10 | 0.12 | -0.07 | 0.17 |
| Data end | 2022 | 0.25 | 0.118 | 0.13 | -0.08 | 0.19 |
| *End-start (annualized)* | 24 | 0.2% | *0.1%* | *0.0%* | *0.0%* | *0.1%* |
| *2015-max (annualized)* | 12 | -1.4% | *-1.5%* | *0.1%* | *0.0%* | *-1.4%* |
| *End-2015 (annualized)* | 7 | 0.4% | *0.2%* | *0.2%* | *-0.1%* | *0.3%* |
| **Uruguay** | | | | | | |
| Data start | 1989 | 0.27 | -0.109 | 0.38 | -0.21 | 0.10 |
| Ratio/year max | 2005 | 0.35 | 0.17 | 0.18 | -0.10 | 0.27 |
| 2015 | 2015 | 0.26 | 0.08 | 0.18 | -0.10 | 0.18 |
| Data end | 2020 | 0.28 | 0.100 | 0.18 | -0.10 | 0.20 |
| *End-start (annualized)* | 31 | 0.0% | *0.7%* | *-0.6%* | *0.4%* | *0.3%* |
| *2015-max (annualized)* | 10 | -0.8% | *-0.9%* | *0.1%* | *0.0%* | *-0.9%* |
| *End-2015 (annualized)* | 5 | 0.3% | *0.4%* | *-0.2%* | *0.1%* | *0.3%* |
| **Average** | | | | | | |
| *End-start (annualized)* | 30 | 0.00% | 0.24% | -0.24% | 0.14% | 0.10% |
| *2015-max (annualized)* | 13 | -0.92% | -0.69% | -0.23% | 0.13% | -0.82% |
| *End-2015 (annualized)* | 6 | -0.18% | 0.07% | -0.25% | 0.14% | -0.07% |
| **Median** | | | | | | |
| *End-start (annualized)* | 30 | 0.04% | 0.30% | -0.26% | 0.15% | 0.14% |
| *2015-max (annualized)* | 12 | -0.71% | -0.12% | -0.33% | 0.19% | -0.43% |
| *End-2015 (annualized)* | 7 | 0.05% | 0.13% | -0.30% | 0.17% | 0.15% |

**Table A5: Wages, supply, demand, and directed technical change ($\sigma = 1.75$, high vs low).**

| | Year | Wage Ratio | Log Wage Ratio | Labor Force Ratio | Log Labor Force Ratio (relative supply) | Katz Murphy Log Demand Ratio | Log Directed Technical Change | Adjusted Log Demand Ratio |
|---|---|---|---|---|---|---|---|---|
| **Argentina** | | | | | | | | |
| Data start | 1992 | 2.24 | 0.35 | 0.37 | -0.43 | 0.19 | -0.24 | 0.43 |
| Ratio/year max | 1998 | 2.81 | 0.45 | 0.46 | -0.34 | 0.44 | -0.19 | 0.64 |
| 2015 | 2016-II | 2.10 | 0.32 | 1.14 | 0.06 | 0.62 | 0.03 | 0.59 |
| Data end | 2023-I | 2.01 | 0.30 | 1.68 | 0.23 | 0.76 | 0.13 | 0.63 |
| *End-start* | *31* | *-0.23* | *-0.05* | *1.31* | *0.65* | *0.57* | *0.37* | *0.20* |
| *2015-max* | *18* | *-0.71* | *-0.13* | *0.69* | *0.40* | *0.18* | *0.23* | *-0.05* |
| *End-2015* | *7* | *-0.08* | *-0.02* | *0.54* | *0.17* | *0.14* | *0.09* | *0.04* |
| **Bolivia** | | | | | | | | |
| Data start | 1997 | 3.30 | 0.52 | 0.25 | -0.60 | 0.30 | -0.34 | 0.64 |
| Ratio/year max | 2000 | 4.91 | 0.69 | 0.29 | -0.54 | 0.67 | -0.30 | 0.97 |
| 2015 | 2015 | 2.10 | 0.32 | 0.53 | -0.27 | 0.29 | -0.15 | 0.44 |
| Data end | 2021 | 2.21 | 0.34 | 0.83 | -0.08 | 0.52 | -0.04 | 0.57 |
| *End-start* | *24* | *-1.09* | *-0.17* | *0.58* | *0.52* | *0.22* | *0.29* | *-0.08* |
| *2015-max* | *15* | *-2.81* | *-0.37* | *0.24* | *0.27* | *-0.38* | *0.15* | *-0.53* |
| *End-2015* | *6* | *0.10* | *0.02* | *0.30* | *0.20* | *0.23* | *0.11* | *0.12* |
| **Brazil** | | | | | | | | |
| Data start | 1981 | 5.57 | 0.75 | 0.07 | -1.17 | 0.14 | -0.66 | 0.79 |
| Ratio/year max | 1988 | 6.80 | 0.83 | 0.09 | -1.05 | 0.40 | -0.59 | 1.00 |
| 2015 | 2015 | 4.29 | 0.63 | 0.34 | -0.46 | 0.64 | -0.26 | 0.90 |
| Data end | 2022 | 3.19 | 0.50 | 0.59 | -0.23 | 0.65 | -0.13 | 0.78 |
| *End-start* | *41* | *-2.37* | *-0.24* | *0.52* | *0.94* | *0.52* | *0.53* | *-0.01* |
| *2015-max* | *27* | *-2.50* | *-0.20* | *0.26* | *0.59* | *0.24* | *0.33* | *-0.09* |
| *End-2015* | *7* | *-1.10* | *-0.13* | *0.25* | *0.24* | *0.01* | *0.13* | *-0.12* |
| **Costa Rica** | | | | | | | | |
| Data start | 1989 | 2.92 | 0.47 | 0.13 | -0.90 | -0.08 | -0.51 | 0.42 |
| Ratio/year max | 2013 | 3.50 | 0.54 | 0.41 | -0.39 | 0.57 | -0.22 | 0.78 |
| 2015 | 2015 | 3.28 | 0.52 | 0.38 | -0.43 | 0.48 | -0.24 | 0.72 |
| Data end | 2023 | 3.02 | 0.48 | 0.51 | -0.29 | 0.55 | -0.16 | 0.71 |
| *End-start* | *34* | *0.09* | *0.01* | *0.38* | *0.61* | *0.63* | *0.34* | *0.29* |
| *2015-max* | *2* | *-0.22* | *-0.03* | *-0.04* | *-0.04* | *-0.09* | *-0.02* | *-0.07* |
| *End-2015* | *8* | *-0.26* | *-0.04* | *0.14* | *0.13* | *0.07* | *0.08* | *0.00* |
| **Honduras** | | | | | | | | |
| Data start | 1991 | 4.72 | 0.67 | 0.04 | -1.35 | -0.17 | -0.76 | 0.59 |
| Ratio/year max | 1992 | 5.14 | 0.71 | 0.05 | -1.31 | -0.07 | -0.74 | 0.67 |
| 2015 | 2015 | 3.52 | 0.55 | 0.11 | -0.96 | -0.01 | -0.54 | 0.53 |
| Data end | 2019 | 3.66 | 0.56 | 0.16 | -0.80 | 0.18 | -0.45 | 0.64 |
| *End-start* | *28* | *-1.05* | *-0.11* | *0.11* | *0.55* | *0.36* | *0.31* | *0.05* |
| *2015-max* | *23* | *-1.62* | *-0.16* | *0.06* | *0.35* | *0.06* | *0.20* | *-0.14* |
| *End-2015* | *4* | *0.15* | *0.02* | *0.05* | *0.16* | *0.19* | *0.09* | *0.10* |
| **Mexico** | | | | | | | | |
| Data start | 1994 | 4.15 | 0.62 | 0.17 | -0.76 | 0.32 | -0.43 | 0.75 |
| Ratio/year max | 2000 | 4.46 | 0.65 | 0.26 | -0.58 | 0.55 | -0.33 | 0.88 |
| 2015 | 2016 | 3.44 | 0.54 | 0.56 | -0.25 | 0.69 | -0.14 | 0.83 |
| Data end | 2020 | 2.95 | 0.47 | 0.74 | -0.13 | 0.69 | -0.07 | 0.76 |
| *End-start* | *26* | *-1.20* | *-0.15* | *0.57* | *0.63* | *0.37* | *0.36* | *0.02* |
| *2015-max* | *16* | *-1.03* | *-0.11* | *0.30* | *0.33* | *0.13* | *0.19* | *-0.05* |
| *End-2015* | *4* | *-0.49* | *-0.07* | *0.18* | *0.12* | *0.01* | *0.07* | *-0.06* |
| **Panama** | | | | | | | | |
| Data start | 1989 | 3.30 | 0.52 | 0.25 | -0.60 | 0.31 | -0.34 | 0.64 |
| Ratio/year max | 2004 | 3.68 | 0.57 | 0.47 | -0.33 | 0.66 | -0.19 | 0.85 |
| 2015 | 2015 | 3.20 | 0.51 | 0.84 | -0.08 | 0.81 | -0.04 | 0.85 |
| Data end | 2023 | 2.78 | 0.44 | 1.11 | 0.05 | 0.82 | 0.03 | 0.80 |
| *End-start* | *34* | *-0.52* | *-0.07* | *0.86* | *0.65* | *0.52* | *0.36* | *0.15* |
| *2015-max* | *11* | *-0.48* | *-0.06* | *0.37* | *0.25* | *0.15* | *0.14* | *0.00* |
| *End-2015* | *8* | *-0.42* | *-0.06* | *0.27* | *0.12* | *0.02* | *0.07* | *-0.05* |
| **Paraguay** | | | | | | | | |
| Data start | 1995 | 3.45 | 0.54 | 0.10 | -0.99 | -0.04 | -0.55 | 0.51 |
| Ratio/year max | 1997 | 4.62 | 0.66 | 0.12 | -0.91 | 0.25 | -0.51 | 0.76 |
| 2015 | 2015 | 2.65 | 0.42 | 0.46 | -0.34 | 0.40 | -0.19 | 0.59 |
| Data end | 2023 | 2.06 | 0.31 | 0.75 | -0.12 | 0.42 | -0.07 | 0.49 |
| *End-start* | *28* | *-1.39* | *-0.22* | *0.65* | *0.86* | *0.47* | *0.48* | *-0.02* |
| *2015-max* | *18* | *-1.97* | *-0.24* | *0.34* | *0.57* | *0.15* | *0.32* | *-0.17* |
| *End-2015* | *8* | *-0.59* | *-0.11* | *0.29* | *0.22* | *0.02* | *0.12* | *-0.10* |
| **Peru** | | | | | | | | |
| Data start | 1998 | 2.64 | 0.42 | 0.40 | -0.39 | 0.34 | -0.22 | 0.56 |
| Ratio/year max | 2003b | 3.83 | 0.58 | 0.48 | -0.32 | 0.70 | -0.18 | 0.88 |
| 2015 | 2015 | 2.39 | 0.38 | 0.70 | -0.16 | 0.51 | -0.09 | 0.60 |
| Data end | 2022 | 2.25 | 0.35 | 0.80 | -0.10 | 0.52 | -0.06 | 0.57 |
| *End-start* | *24* | *-0.39* | *-0.07* | *0.39* | *0.30* | *0.17* | *0.17* | *0.01* |
| *2015-max* | *12* | *-1.43* | *-0.20* | *0.22* | *0.17* | *-0.19* | *0.09* | *-0.28* |
| *End-2015* | *7* | *-0.15* | *-0.03* | *0.10* | *0.06* | *0.01* | *0.03* | *-0.02* |
| **Uruguay** | | | | | | | | |
| Data start | 1989 | 2.69 | 0.43 | 0.11 | -0.95 | -0.20 | -0.54 | 0.34 |
| Ratio/year max | 2004 | 3.44 | 0.54 | 0.45 | -0.34 | 0.60 | -0.19 | 0.79 |
| 2015 | 2015 | 2.38 | 0.38 | 0.52 | -0.29 | 0.37 | -0.16 | 0.53 |
| Data end | 2020 | 2.34 | 0.37 | 0.68 | -0.17 | 0.48 | -0.10 | 0.57 |
| *End-start* | *31* | *-0.34* | *-0.06* | *0.56* | *0.78* | *0.68* | *0.44* | *0.24* |
| *2015-max* | *11* | *-1.06* | *-0.16* | *0.06* | *0.06* | *-0.23* | *0.03* | *-0.26* |
| *End-2015* | *5* | *-0.03* | *-0.01* | *0.16* | *0.12* | *0.11* | *0.07* | *0.04* |
| **Average** | | | | | | | | |
| *End-start* | 30 | -0.85 | -0.11 | 0.59 | 0.65 | 0.45 | 0.37 | 0.09 |
| *2015-max* | 15 | -1.38 | -0.17 | 0.25 | 0.29 | 0.00 | 0.17 | -0.16 |
| *End-2015* | 6 | -0.29 | -0.04 | 0.23 | 0.15 | 0.08 | 0.09 | -0.01 |
| **Median** | | | | | | | | |
| *End-start* | 30 | -0.79 | -0.09 | 0.57 | 0.64 | 0.49 | 0.36 | 0.03 |
| *2015-max* | 16 | -1.25 | -0.16 | 0.25 | 0.30 | 0.10 | 0.17 | -0.11 |
| *End-2015* | *7* | *-0.21* | *-0.03* | *0.22* | *0.15* | *0.05* | *0.08* | *-0.01* |

**Table A6: Contributions to Wage Ratios ($\sigma = 1.75$, high vs low).**

| | Year | Log Wage Ratio | Unadjusted Log Demand | Log Supply (substitution) | Log Directed Technical Change | Adjusted Log Demand |
|---|---|---|---|---|---|---|
| **Argentina** | | | | | | |
| Data start | 1992 | 0.35 | 0.11 | 0.24 | -0.14 | 0.24 |
| Ratio/year max | 1998 | 0.45 | 0.25 | 0.20 | -0.11 | 0.36 |
| 2015 | 2016-II | 0.32 | 0.36 | -0.03 | 0.02 | 0.34 |
| Data end | 2023-I | 0.30 | 0.43 | -0.13 | 0.07 | 0.36 |
| *End-start (annualized)* | 31 | -0.2% | *1.1%* | *-1.2%* | *0.7%* | *0.4%* |
| *2015-max (annualized)* | 18 | -0.7% | *0.6%* | *-1.3%* | *0.7%* | *-0.2%* |
| *End-2015 (annualized)* | 7 | -0.3% | *1.1%* | *-1.4%* | *0.8%* | *0.3%* |
| **Bolivia** | | | | | | |
| Data start | 1997 | 0.52 | 0.17 | 0.34 | -0.19 | 0.37 |
| Ratio/year max | 2000 | 0.69 | 0.38 | 0.31 | -0.17 | 0.56 |
| 2015 | 2015 | 0.32 | 0.17 | 0.16 | -0.09 | 0.25 |
| Data end | 2021 | 0.34 | 0.30 | 0.04 | -0.03 | 0.32 |
| *End-start (annualized)* | 24 | -0.7% | *0.5%* | *-1.2%* | *0.7%* | *-0.2%* |
| *2015-max (annualized)* | 15 | -2.5% | *-1.4%* | *-1.0%* | *0.6%* | *-2.0%* |
| *End-2015 (annualized)* | 6 | 0.3% | *2.2%* | *-1.9%* | *1.0%* | *1.2%* |
| **Brazil** | | | | | | |
| Data start | 1981 | 0.75 | 0.08 | 0.67 | -0.38 | 0.45 |
| Ratio/year max | 1988 | 0.83 | 0.23 | 0.60 | -0.34 | 0.57 |
| 2015 | 2015 | 0.63 | 0.37 | 0.26 | -0.15 | 0.52 |
| Data end | 2022 | 0.50 | 0.37 | 0.13 | -0.07 | 0.45 |
| *End-start (annualized)* | 41 | -0.6% | *0.7%* | *-1.3%* | *0.7%* | *0.0%* |
| *2015-max (annualized)* | 27 | -0.7% | *0.5%* | *-1.2%* | *0.7%* | *-0.2%* |
| *End-2015 (annualized)* | 7 | -1.8% | *0.1%* | *-1.9%* | *1.1%* | *-1.0%* |
| **Costa Rica** | | | | | | |
| Data start | 1989 | 0.47 | -0.05 | 0.51 | -0.29 | 0.24 |
| Ratio/year max | 2013 | 0.54 | 0.32 | 0.22 | -0.12 | 0.45 |
| 2015 | 2015 | 0.52 | 0.27 | 0.24 | -0.14 | 0.41 |
| Data end | 2023 | 0.48 | 0.31 | 0.17 | -0.09 | 0.41 |
| *End-start (annualized)* | 34 | 0.0% | *1.1%* | *-1.0%* | *0.6%* | *0.5%* |
| *2015-max (annualized)* | 2 | -1.4% | *-2.6%* | *1.1%* | *-0.6%* | *-1.9%* |
| *End-2015 (annualized)* | 8 | -0.5% | *0.5%* | *-1.0%* | *0.5%* | *0.0%* |
| **Honduras** | | | | | | |
| Data start | 1991 | 0.67 | -0.10 | 0.77 | -0.43 | 0.34 |
| Ratio/year max | 1992 | 0.71 | -0.04 | 0.75 | -0.42 | 0.38 |
| 2015 | 2015 | 0.55 | 0.00 | 0.55 | -0.31 | 0.31 |
| Data end | 2019 | 0.56 | 0.11 | 0.46 | -0.26 | 0.36 |
| *End-start (annualized)* | 28 | -0.4% | *0.7%* | *-1.1%* | *0.6%* | *0.1%* |
| *2015-max (annualized)* | 23 | -0.7% | *0.1%* | *-0.9%* | *0.5%* | *-0.3%* |
| *End-2015 (annualized)* | 4 | 0.4% | *2.7%* | *-2.3%* | *1.3%* | *1.4%* |
| **Mexico** | | | | | | |
| Data start | 1994 | 0.62 | 0.18 | 0.44 | -0.25 | 0.43 |
| Ratio/year max | 2000 | 0.65 | 0.32 | 0.33 | -0.19 | 0.50 |
| 2015 | 2016 | 0.54 | 0.39 | 0.14 | -0.08 | 0.47 |
| Data end | 2020 | 0.47 | 0.40 | 0.07 | -0.04 | 0.44 |
| *End-start (annualized)* | 26 | -0.6% | *0.8%* | *-1.4%* | *0.8%* | *0.0%* |
| *2015-max (annualized)* | 16 | -0.7% | *0.5%* | *-1.2%* | *0.7%* | *-0.2%* |
| *End-2015 (annualized)* | 4 | -1.7% | *0.1%* | *-1.8%* | *1.0%* | *-0.9%* |
| **Panama** | | | | | | |
| Data start | 1989 | 0.52 | 0.18 | 0.34 | -0.19 | 0.37 |
| Ratio/year max | 2004 | 0.57 | 0.38 | 0.19 | -0.11 | 0.48 |
| 2015 | 2015 | 0.51 | 0.46 | 0.04 | -0.02 | 0.49 |
| Data end | 2023 | 0.44 | 0.47 | -0.03 | 0.01 | 0.46 |
| *End-start (annualized)* | 34 | -0.2% | *0.9%* | *-1.1%* | *0.6%* | *0.3%* |
| *2015-max (annualized)* | 11 | -0.6% | *0.8%* | *-1.3%* | *0.7%* | *0.0%* |
| *End-2015 (annualized)* | 8 | -0.8% | *0.1%* | *-0.9%* | *0.5%* | *-0.4%* |
| **Paraguay** | | | | | | |
| Data start | 1995 | 0.54 | -0.03 | 0.56 | -0.32 | 0.29 |
| Ratio/year max | 1997 | 0.66 | 0.14 | 0.52 | -0.29 | 0.44 |
| 2015 | 2015 | 0.42 | 0.23 | 0.19 | -0.11 | 0.34 |
| Data end | 2023 | 0.31 | 0.24 | 0.07 | -0.04 | 0.28 |
| *End-start (annualized)* | 28 | -0.8% | *1.0%* | *-1.8%* | *1.0%* | *0.0%* |
| *2015-max (annualized)* | 18 | -1.3% | *0.5%* | *-1.8%* | *1.0%* | *-0.5%* |
| *End-2015 (annualized)* | 8 | -1.4% | *0.2%* | *-1.5%* | *0.9%* | *-0.7%* |
| **Peru** | | | | | | |
| Data start | 1998 | 0.42 | 0.20 | 0.23 | -0.13 | 0.32 |
| Ratio/year max | 2003b | 0.58 | 0.40 | 0.18 | -0.10 | 0.50 |
| 2015 | 2015 | 0.38 | 0.29 | 0.09 | -0.05 | 0.34 |
| Data end | 2022 | 0.35 | 0.29 | 0.06 | -0.03 | 0.33 |
| *End-start (annualized)* | 24 | -0.3% | *0.4%* | *-0.7%* | *0.4%* | *0.0%* |
| *2015-max (annualized)* | 12 | -1.7% | *-0.9%* | *-0.8%* | *0.4%* | *-1.3%* |
| *End-2015 (annualized)* | 7 | -0.4% | *0.1%* | *-0.5%* | *0.3%* | *-0.2%* |
| **Uruguay** | | | | | | |
| Data start | 1989 | 0.43 | -0.11 | 0.54 | -0.31 | 0.19 |
| Ratio/year max | 2004 | 0.54 | 0.34 | 0.20 | -0.11 | 0.45 |
| 2015 | 2015 | 0.38 | 0.21 | 0.16 | -0.09 | 0.30 |
| Data end | 2020 | 0.37 | 0.27 | 0.10 | -0.05 | 0.33 |
| *End-start (annualized)* | 31 | -0.2% | *1.2%* | *-1.4%* | *0.8%* | *0.4%* |
| *2015-max (annualized)* | 11 | -1.5% | *-1.2%* | *-0.3%* | *0.2%* | *-1.3%* |
| *End-2015 (annualized)* | 5 | -0.1% | *1.2%* | *-1.3%* | *0.8%* | *0.5%* |
| **Average** | | | | | | |
| *End-start (annualized)* | 30 | -0.39% | 0.84% | -1.23% | 0.69% | 0.15% |
| *2015-max (annualized)* | 15 | -1.18% | -0.31% | -0.87% | 0.49% | -0.80% |
| *End-2015 (annualized)* | 6 | -0.61% | 0.83% | -1.44% | 0.81% | 0.02% |
| **Median** | | | | | | |
| *End-start (annualized)* | 30 | -0.34% | 0.85% | -1.23% | 0.69% | 0.07% |
| *2015-max (annualized)* | 16 | -1.04% | 0.31% | -1.10% | 0.62% | -0.44% |
| *End-2015 (annualized)* | 7 | -0.43% | 0.33% | -1.45% | 0.82% | -0.12% |

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