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Heterogeneity of total factor productivity across Latin American countries: evidence from manufacturing firms*

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Abstract

We use a firm production function approach to generate estimates of total factor productivity (TFP) and labor productivity in the manufacturing sector for a group of Latin American countries. We exploit these estimates to study the relative position of countries within this sector and to explore the main correlates of firm productivity. We find that while the exact ranking of average TFP is sensitive to the underlying form of the production function, Chile and Argentina average level of TFP is found to be consistently above that of other countries, while Bolivia firms always appears at the bottom of the distribution. While other aspects matter, the main factors explaining differences in productivity across firms are related to country-level, not firm-level, characteristics.

JEL classification: D24, D22, C23.
Keywords: Total Factor Productivity, Multi Factor Productivity, Labor Productivity, Latin America.

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1 Introduction

Latin America (LA) is an important region of the world to understand economic development. Conformed by a group of lower and upper middle-income countries, its economies are typically considered a benchmark for less developed countries around the world. Yet there is significant heterogeneity within the region –in terms of income per capita, poverty levels, financial development, etc. In this study we consider the issue of total factor productivity (TFP) heterogeneity across Latin American countries, with a focus on the manufacturing sector. While the relative importance of manufacturing has decreased over time in this region (and in the developing world), its importance can not be neglected: in 2010, it represented approximately 16 per cent of the GDP of LA and the Caribbean.[1] The manufacturing sector is particularly attractive because data availability allows us to implement –and the structure of the sector allow us to justify– the use a firm production function approach.

Although TFP measures are imprecise for a number of reasons including aggregation and functional form assumptions, the use of firm-level data for its estimation offers some functional advantages: (a) it provides the means to characterize heterogeneity in the production function –factor elasticities are likely to vary by country and by sub-sector within manufacturing; (b) it provides a natural way to test for differences across countries because the whole distribution of productivity within countries is observed; and, (c) it gives scope to study factors associated with productivity. Consequently, firm-level estimates of the TFP can lead to a better understanding of the differences in economic performance across countries.

For our analysis, we use data from the *World Bank's Enterprise Surveys* of 2006 and 2010 for the following countries: Argentina, Bolivia, Colombia, Chile, Ecuador, Mexico, Paraguay, Peru and Uruguay.[2] This data is informative of firm's performance in 2005 and 2009, respectively. We use this data to achieve four objectives. First, we report differences in the factor elasticities between countries. Second, we produce estimates of productivity levels (TFP and labour productivity) and use these results to produce country rankings, for manufacturing as a whole and distinguishing between the main sub-sectors that we observe (*food products and beverages*, *textiles*, *wearing apparel and dressing* and *chemicals*). Third, we explore to what extent

[1]Source: World Development Indicators.

[2]Although information is available for the manufacturing and trade sectors, we concentrate on the former because the data collected is richer for this sector.

firm productivity is explained by firm-level characteristics and by country, city and sub-sector characteristics of a time-invariant nature. To our knowledge, this is the first study of its kind for the LA region. For similar studies in other parts of the world see, for instance, Fernandes (2008), Bigsten and ns Söderbom (2006) and Subramanian et al. (2005).

In terms of the methodology, we use a two-factor Cobb-Douglas production function as the baseline specification, with parameters assumed constant at the country-level and over time. We use this specification to estimate factor elasticities for each country sample by OLS. Then, we use these estimated coefficients to calculate the TFP of each firm in each country. This allows us to depict differences in the distribution of the TFP across the observed countries, including comparisons of average productivity levels and stochastic dominance analysis. We are aware of the limitations that this strategy might have, particularly the problem of omitted variables. To check for the robustness of the results we test a number of variations of the baseline model, including refined measures of the production factors and an extended three-factor model. This turns out to be extremely useful to understand the extent to which country rankings can be sensitive to functional form assumptions. In addition, we exploit the panel nature of the data to produce firm fixed-effect estimations of the production function as a way to deal with potential omitted variables at the firm level.

Based on this strategy, we obtain estimates for factor elasticities which are consistent with those reported in the cross-country literature (Nehru et al., 1994). Using these values to estimate TFP at the firm-level and, then, to compare the average TFP of the manufacturing sector in each country, we find country rankings to be sensitive to the underlying form of the production function. However, it seems clear that Argentina's and Chile's average TFP level is above that of the other countries studied. Similarly, Bolivia consistently appears at the bottom of the distribution in all the specifications. As expected, countries with low GDP per capita tend to have lower TFP. Our results at the micro level resemble those obtained by IADB (2010) which uses data from national accounts to estimate the aggregate productivity of these economies.

In terms of the factors associated to TFP, we find that while aspects such as firm's size, export status, presence of foreign capital and access to credit markets matter, the main factor explaining differences in productivity across firms is related to country-level characteristics. That is, productivity is mainly driven by factors largely out of the control of the firm.

The paper is organized as follows. Section 2 describes our empirical methodology. Section 3 describes the data used for the analysis. Section 4 presents our findings and Section 5 concludes.

2 Empirical Methodology

A large amount of literature has revolved around the estimation of production functions and the recovery of factor elasticities using firm-level data. See Griliches and Mairesse (1995) for a detailed, critical, review. A central aspect is under which conditions factor elasticities can be identified. Consider the log-linearized version of a production function of the Cobb-Douglas form,

$$y_t = a_t + \alpha_k k_t + \alpha_l l_t + \epsilon_t \tag{1}$$

where α_k and α_l are the factor elasticities, k and l are the physical and labour factors used in year t, y_t is output produced in year t, a_t is productivity and ϵ_t is measurement error. As usual, a_t is unobserved to the econometrician. Assuming this is the true production function, consistent estimations of α_k and α_l can be obtained by OLS only under certain assumptions. If the firm observes a_t and inputs are perfectly flexible, then it could choose k_t and l_t accordingly, rendering OLS estimates of α_k and α_l inconsistent. As noted in the literature, if both inputs are costly to adjust, the identification problem becomes less acute (Bond and ns Söderbom, 2005). One could also assume that profit maximization takes place *ex-ante* (before a_t is realized), which also solves the problem. Even if this is the case, in practice, there could be unobserved inputs. For instance, the number of workers of the firm might be an imperfect measure of the labour factor if there is heterogeneity in the education profile of workers between firms in the same sector.

Different strategies have been proposed in the literature for the identification of factor elasticities if it is suspected that inputs are perfectly flexible and/or if there are unobserved inputs. One alternative is to implement an instrumental variables strategy using input prices of k_t and l_t as instruments for k_t and l_t, respectively (Mundlak, 1961). Another alternative is to implement a within-firms estimation strategy, which deals with time-invariant unobservables. In addition, structural procedures (Olley and Pakes, 1996; Levinsohn and Petrin, 2003) and dynamic panel data methods (Blundell and Bond, 1998) have been proposed that require panel data with at least three periods. Considering the available data, we opted for using OLS and firm fixed effects methods to produce estimates of α_k and α_l for each country. As a robustness check, we also report results for two additional specifications of the firm production function that control for the quality of human capital: a 2-factor model with the labor factor adjusted by education and a 3-factor model where skilled and unskilled workers are differentiated.

For the estimation we use the following variables. To proxy the capital factor we use information on the book value of the fixed assets owned by the firm, whereas the labor factor is proxied by the number of permanent, full-time employees. To calculate firm output we use gross annual sales as well as gross sales minus the annual cost of the intermediate inputs used in the production process –the added value generated by the firm. Due to sample size considerations, we use the former variable in our baseline specification and report results using the latter variable as part of our robustness checks. All variables that enter the production function are expressed in logs. Also, as part of the robustness checks a distinction is made between skilled and unskilled workers. The group of skilled workers include skilled production workers[3] and all non-production workers. The group of unskilled workers are those production workers that do not require to have special training, education, or skill to perform their job.

3 Data and Descriptive Statistics

3.1 Data

Our analysis uses data from the *World Bank's Enterprise Surveys* 2006 and 2010. These surveys collect firm-level data from manufacturing and service sectors in countries in every region of the world. Data is informative of firm's performance in the previous year (2005 and 2009, respectively). We focus on manufacturing firms only because the available data is richer for firms in this sector.[4] In addition, for our main results we only use data from 2006 because sample sizes were too small for Bolivia, Paraguay and Ecuador (the poorest countries in our sample in terms of GDP per capita) in 2010.[5]

[3]Skilled production workers are those that have some special knowledge or ability in their work. A skilled worker may have attended a college, university or technical school and/or, may have learned his skills on the job.

[4]In particular, good proxies are exclusively available for the capital factor of manufacturing firms.

[5]Sample sizes of 49, 91 and 68 in 2010, respectively. In 2006, sample sizes for these countries were 226, 259 and 240, respectively.

Data used in this study covers Argentina, Bolivia, Chile, Colombia, Ecuador, Mexico, Paraguay, Peru and Uruguay -Brazil was not covered in the 2006 survey, nor in any close year. Each country survey is informative of the universe of firms with at least 5 employees in all the manufacturing sectors.[6] Since the World Bank uses a uniform sampling methodology and standardized instruments, we are able to compare results across these countries. Throughout the analysis, monetary values are converted into PPP US Dollars, making use of the 2005 and 2009 exchange rates published in the World Bank Economic Outlook database.

3.2 Descriptive Statistics

In the 2006 surveys the data covered 3,177 firms.[7] The average firm depicted sales of around 24 million US Dollars per year (Table 1). The highest average sales are found for Mexican companies, with an average revenue of 44.4 million PPP US Dollars, while the lowest average revenue is observed for Paraguayan companies. The largest heterogeneity of revenues is observed in Chile.[8]

Table 1: Summary statistics of sales per company in million PPP USD

Country	Mean	Median	Std. Dev.	Frequency
Argentina	40.1	3.0	193.2	396
Bolivia	9.0	0.7	37.3	226
Chile	27.6	1.7	158.5	401
Colombia	7.7	0.7	46.3	536
Ecuador	10.8	1.8	28.0	250
Mexico	44.4	0.8	1053.3	799
Paraguay	6.5	0.7	46.4	149
Peru	15.9	2.3	64.2	244
Uruguay	8.6	0.9	28.6	176
Total	24.4	1.1	536.4	3,177

Data corresponds to the 2006 surveys.

In terms of the size of the companies according to the number of workers employed, the median company in our sample has around 23 full-time employees, while the average company employs around 100 workers. Argentina

[6]Manufacturing contains codes 15 to 37 of the International Standard Industrial Classification (ISIC).

[7]Observations depicting sales of more than 10 standard deviations above mean sales in the respective country are eliminated from the sample. This concerns a total of 6 companies, which effects exclusively Mexico and Colombia.

[8]A boxplot of log annual sales in USD is shown in Figure 7, Appendix

has the most employees per company, however driven by some very large companies with more than 10,000 employees.

Table 2: Summary statistics of employees per company

Country	Mean	Median	Min	Max
Argentina	208.2	34.0	1	18000
Bolivia	47.9	17.0	3	500
Chile	93.3	30.0	1	4200
Colombia	67.6	18.0	2	3520
Ecuador	71.0	23.0	2	1100
Mexico	116.7	22.0	4	4500
Paraguay	39.4	20.0	4	500
Peru	104.4	28.0	2	1587
Uruguay	44.0	21.0	3	640
Total	99.8	23	1	18000

Data corresponds to the 2006 surveys.

4 Results

4.1 Factor elasticities

We start by reporting the factor elasticities obtained for each country sample (Table 3).[9] The first two columns (Panel 1) report results for the baseline specification, i.e., a Cobb-Douglas production function. As an example, for Peru we obtain values of α_k and α_l of 0.39 and 0.61, respectively. Three aspects of the results are worth highlighting. First, results show that the manufacturing industry in the selected countries is relatively labor intensive. Second, there seems to be considerable heterogeneity across countries. Argentina and Chile are found to be the least labor intensive, whereas Peru and Bolivia are most labor intensive. Third, with the exception of Argentina, results are largely in line with elasticities estimated from cross-country studies. For instance, based on a sample of 67 low and middle income countries, Nehru et al. (1994) calculate a point estimate of the capital elasticity of 0.38 for the average economy, similar to our estimate for countries such as Bolivia, Ecuador and Peru.

As mentioned before, the estimates depicted in the baseline specification are likely to suffer from certain biases. The most natural reason for the

[9]For the estimations reported above, we imposed the constraint that elasticities should sum up to 1.

Table 3: Factor Elasticities

Country	2-factors		2-factors (labour adjusted by education)		3-factors		
	Panel 1 ***Baseline***		Panel 2		Panel 3		
	α_k	α_l	α_k	α_l	α_k	α_l^s	α_l^u
Argentina	0.16	0.84	0.22	0.78	0.20	0.69	0.11
Bolivia	0.40	0.60	0.43	0.57	0.40	0.44	0.16
Chile	0.19	0.81	0.23	0.77	0.22	0.64	0.14
Colombia	0.23	0.77	0.33	0.67	0.25	0.56	0.19
Ecuador	0.34	0.66	0.40	0.60	0.33	0.62	0.05
Mexico	0.25	0.75	0.26	0.74	0.28	0.68	0.05
Paraguay	0.25	0.75	0.29	0.71	0.26	0.48	0.26
Peru	0.39	0.61	0.44	0.56	0.40	0.49	0.10
Uruguay	0.31	0.69	0.43	0.57	0.34	0.61	0.05

Note: The output of the firm is proxied by gross annual sales. The book value of fixed assets is used to proxy the capital factor. In Panel 1, the labor factor is the number of full-time employees. In Panel 2, this value is multiplied by the average years of education of workers. In Panel 3, the labor force is disaggregated into skilled and unskilled workers.

implied parameters in the baseline model to be biased are that the implicit orthogonal technology assumption in our model is not a good approximation to reality. One example of an omitted variable in the previous specification is the quality of human capital that firms make use of. There might be other omitted variables as well. To partially deal with these aspects, we estimate two alternative models that adjust the labour factor by the quality of human capital: a 2-factor model with labor adjusted by years of education (Panel 2) and a 3-factor model that distinguishes between skilled and unskilled workers (Panel 3).

The specification in Panel 2 shows that the elasticity towards the labor factor decreases slightly if average education is taken into account, while the desegregation of unskilled and skilled labor reported in Panel 3 yields nearly similar elasticities to labor and capital as the baseline specification. As can be seen, α_l (baseline) $>$ (α_l^s $+\alpha_l^u$) $>$ α_l (adjusted by average education). This result could be driven by a slight misidentification of the model if education is represented as average education. While both specifications confirm the elasticities observed in the baseline model, the better alternative between both robustness checks is to divide labor in skilled and unskilled.[10] With regards to the following TFP estimations, we keep our baseline model in the light of a higher frequency of observations and sufficiently small elasticity

[10]Elasticities are also robust across various measures of output and capital.

differences with respect to the other two specifications presented.[11]

4.1.1 Factor elasticities with firm fixed effects

As a further robustness check we also consider the calculation of factor elasticities from an estimation with firm fixed effects applied to a panel of firms observed in 2006 and 2010.[12] Due to sample size considerations this is implemented only for the cases of Argentina, Chile, Colombia and Peru.[13] While this approach is theoretically attractive since it allows to control for firm characteristics that are time invariant, a practical limitation exists since results rely on the existence of meaningful temporal variation in the inputs. One might suspect that capital in the form of fixed assets varies little over time, which in turn might have consequences for the calculation of the parameters by giving a more important role to the flexible input as an explanatory factor. Anticipating this problem, results are also reported using an alternative proxy for the input capital: the annual cost of energy used by the firm. One can reasonably expect this variable to better reflect changes in the use of capital of the firm over time.

The factor elasticities obtained are reported in Table 4 in the Appendix. As can be observed, pooled OLS (Column 1) and firm fixed effects estimates (Column 2) lead to very different results when capital is proxied by the value of assets, with a much smaller contribution of capital in the latter case. Column 3 reports results using the annual cost of energy used by the firm as a proxy of the capital factor. When doing this, we find that in 3 out of 4 countries for which panel data is available the elasticities obtained with OLS and fixed effects are similar. The only exception is Colombia. This gives us ground to claim that the factor elasticities obtained with OLS do not appear to be significantly biased due to time-invariant firm unobservable characteristics.

[11] Robustness checks on the basis of both alternative specifications are provided in the Appendix.

[12] A balanced panel is used because only for those firms we can argue that time-invariant firm level unobservables can be removed.

[13] After missing values, country sample sizes are as follow: 141 firms in Argentina, 121 in Chile, 130 in Colombia and 82 in Peru. In the other countries panel samples are below 30 firms.

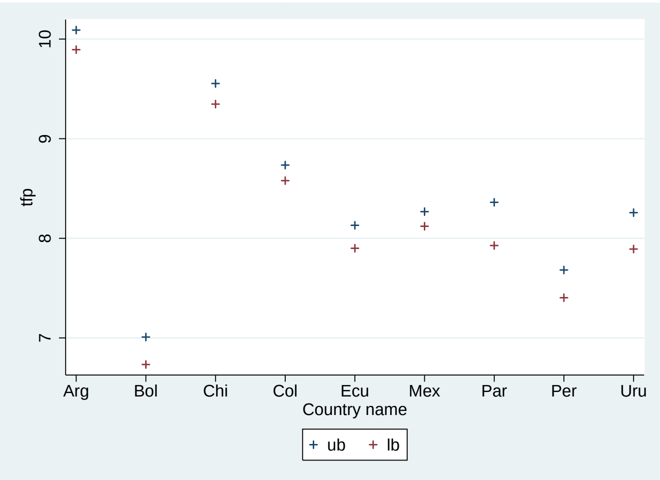
4.2 Estimates of TFP

We calculate the TFP of each firm as the residual of the production function, where the factor elasticities are those estimated previously by OLS (baseline specification). That is,

$$TFP_{i,j,t} = y_{i,j,t} - \hat{\alpha}_{k,j} k_{i,j,t} - \hat{\alpha}_{l,j} l_{i,j,t} \tag{2}$$

where i is a firm from country j observed in period t and $\hat{\alpha}_{k,j}$ and $\hat{\alpha}_{l,j}$ are country-specific, time-invariant OLS estimates of capital and labor factor elasticities, respectively. As a way to compactly report our results, Figure 1 reports the confidence intervals (lower and upper bounds) of the average TFP in each country using the baseline specification.[14] While results correspond to one particular sector of the economiy, a positive correlation between average TFP and GDP per capita becomes apparent (see Figure 2).

Figure 1: Baseline results (average TFP confidence intervals)

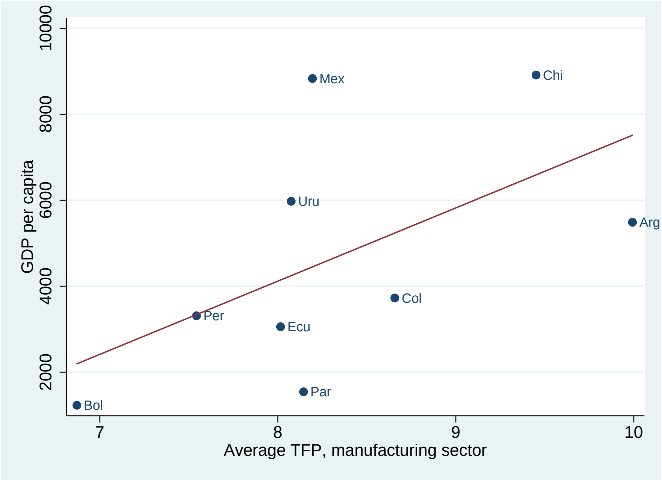


Note: Markers denote the confidence interval in which the average TFP of each country sample is located at the 95% level.

The same results obtained for alternative model specifications are reported in Figure 8 in the Appendix, in which, in addition to the 2-factors and 3-factors models that adjust the labour factor by the quality of human capital,

[14] The point estimates of the elasticities used for the calculation of the TFP for each firm are those reported in Table 3, Panel 1.

Figure 2: GDP per capita and average TFP (baseline results)



Note: The line denotes the slope of a least square regression linking GDP per capita and average TFP.

we report separate results using gross sales and added value (gross sales minus the cost of intermediate inputs) as the output of the firm. While the exact ranking of countries is found to be sensitive to the model specification used, a pattern emerges, with Argentina and Chile depicting the highest average TFP, whereas Bolivia ranks at the bottom of the distribution. Differences in average TFP are significant between Chile and Argentina, and the other countries studied.[15] The remaining Latin American countries constitute an intermediate group, where, depending on the estimation specification, Colombia is found on the upper bound of the intermediate group, with Ecuador, Mexico, Paraguay, and Uruguay following closely and with Peru (a country with a low GDP per capita) typically below all of these countries. Confidence intervals for this intermediate group of countries cross depending on the model specification applied.

To check to what extent these results are driven by heterogeneity in factor elasticities across countries, we report results imposing the same factor elasticities to all countries (see Figure 9 in the Appendix). Using constant elasticities across countries eliminates a large part of the heterogeneity in the sample. Except for Peru however, the relative position of countries does not change. While Argentina and Chile continue at the top of the distribution,

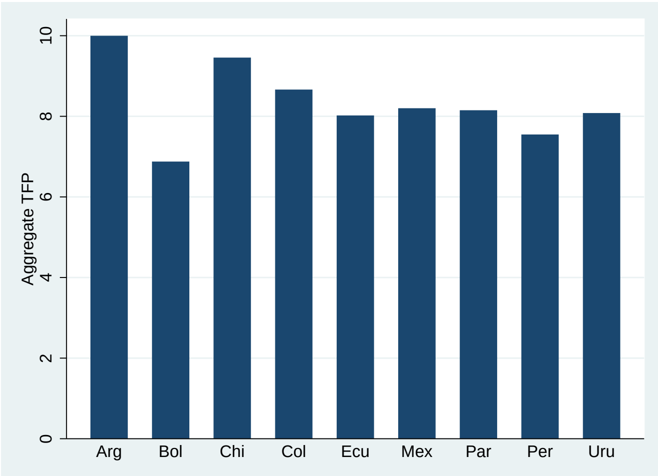
[15]Independent of the measure of output and the specification used. An exception is Paraguay, whose TFP estimation changes once a separation of skilled and unskilled workers is carried out, suggesting large heterogeneity of education both within and across firms.

Bolivia lies at the bottom.

In Figure 10 (Appendix) results are reported independently for the sub-sectors of manufacturing for which we have a relatively high number of observations: (a) *food and beverages*; (b) *textiles*; (c) *wearing apparel and dressing*; and, (d) *chemicals*. Firms from other sub-sectors within manufacturing are classified in a fifth category.[16] If the previously explained average TFP pattern is broken down to sub-sectors, Argentina is found to lead the ranking in all five categories, whereas Bolivia is in the last position in three out of the five categories. Argentina aside, in the sector of *chemicals* and in *other manufacturing firms*, differences between countries are not statistically significant. The second position of Chile in the general ranking seems to be driven by high productivity in *food product and beverages*, *textiles* and *wearing apparel and dressing*.

Turning back towards consolidated figures, aggregate TFP results are reported in Figure 3. The aggregation is carried out by weighting each firm's TFP according to its share of total sales. The relative order of the countries is the same as the one obtained with average TFP. It does therefore not seem to be the case that a few large, high productivity firms could explain the relative ranking of countries.

Figure 3: Baseline results: aggregate TFP



[16]Only sub-sectors for which a minimum of 30 firms are observed in each country are reported. Ecuador, Paraguay and Uruguay and, in the case of textiles, Bolivia, were excluded due to sample size considerations.

4.2.1 A closer look at TFP distributions

In order to compactly compare TFP distributions, box-plots are shown in Figure 4. Mexico depicts the largest heterogeneity, while Chile's variance of estimated TFPs is the smallest. Interestingly, all intermediate countries possess some companies whose productivity level is at least as high as the level of productivity by an average company in the best performing countries.

Figure 4: Baseline results: TFP distributions of average TFP

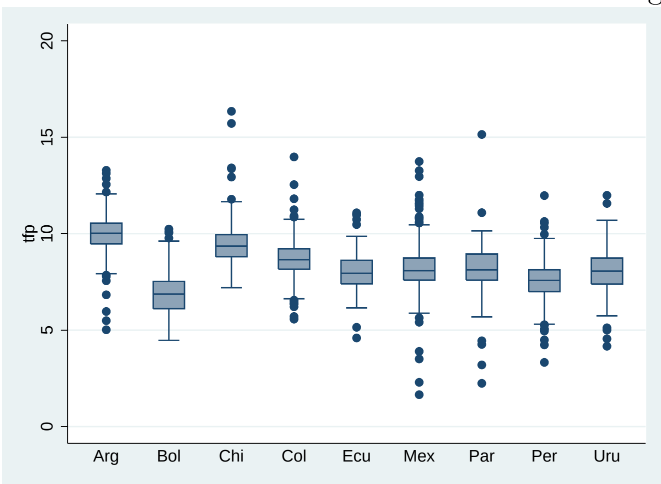
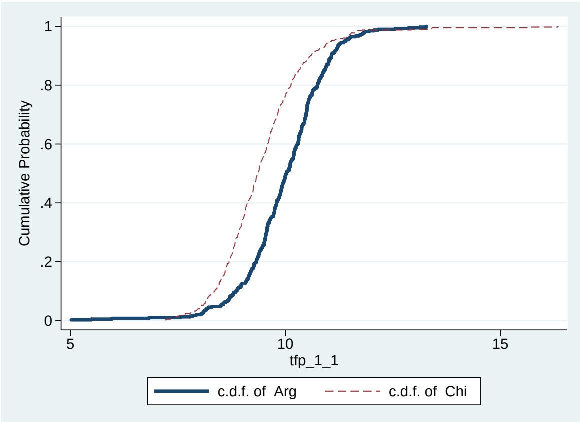


Figure 5 shows cumulative density functions (CDF) for the distributions of TFP in the baseline estimation for pairs of countries chosen for illustrative purposes. In the upper quadrant (a.), one can observe that the two best performing countries, Argentina and Chile, have comparable levels of TFP at nearly all points of the distribution. High and low productivity firms within each of the two countries perform alike, while in the intermediate part of the distribution Argentinian firms slightly outperform Chilean ones.

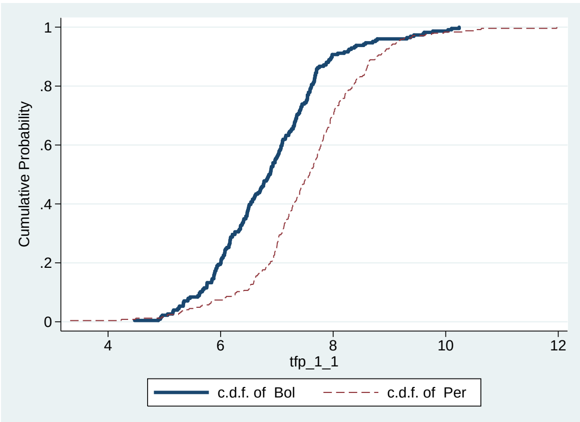
Comparing the two worst performing countries, Peru and Bolivia (b.) , as well as the best performing country, Argentina, with an intermediate productivity country, Uruguay (c.), a pattern emerges. We observe that the heterogeneity observed stems largely from the intermediate parts of TFP distributions, where, for instance, Peruvian companies outperform Bolivian ones, and Argentinean firms outperform Uruguays', while the best and worst performing three percent of both aforementioned countries' firms are comparable in levels of TFP. In all countries, there are some companies being at least as productive as average firms in the best performing countries.

Figure 5: Baseline results: cumulative density functions for selected pairs of countries

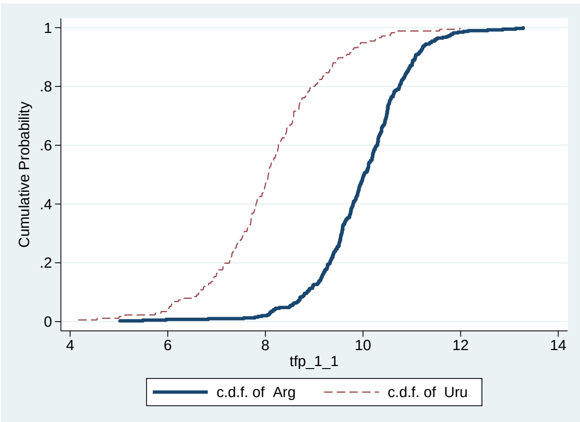
a. Argentina and Chile



b. Peru and Bolivia



c. Argentina and Uruguay

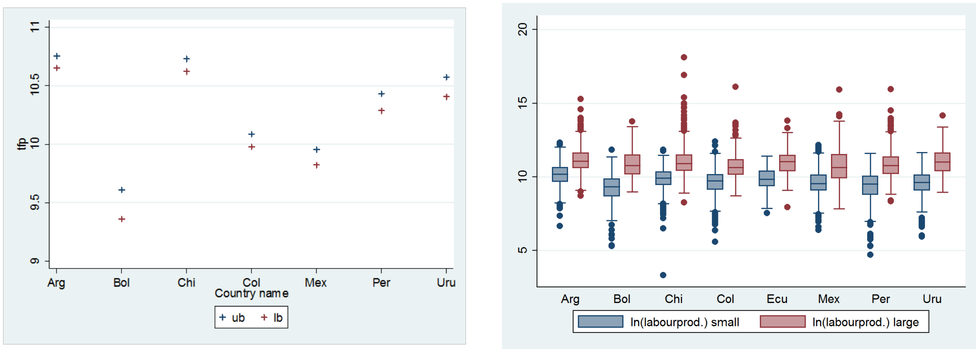


4.3 Labor Productivity

We define labor productivity as value added per full time employee. Labor productivity as a measure of efficiency should be taken with caution, as output can be influenced by various factors outside of the worker's influence, such as the amount of capital and the technology at his disposal.

Figure 6: Labor productivity

a. Confidence interval   b. Labor productivity distribution by firm size



Even though the logarithmic distributions of labor productivity are little heterogenous, average labor productivity confirms the picture drawn in the last section (Figure 6, left column). Argentina and Chile do depict the highest value added per worker, while Bolivia is at the bottom of the distribution. Peru rises in the distribution as compared to its TFP performance and ranks in the upper part of the intermediate group.

The difference of value added per worker is large across firm sizes (Figure 6, right column). While large firms in general outperform small firms in terms of value added per worker[17], the difference in overall country labor productivity does seem to be caused by the distribution of value added per worker for small companies. While e.g. Bolivia's large firms achieve nearly the same labor productivity as Argentinean or Chilean firms, the cumulative distribution of labor productivity of small firms in Bolivia is entirely dominated by that of small firms in either Chile or Argentina. In order to increase labor productivity in the least productive countries, it is therefore important to target on small companies rather than large ones, which are already on a comparable level with the most productive countries.

[17]Large firms are defined to have yearly sales above 1,223,242 USD, which represents median sales in our sample.

4.4 Correlates of TFP

In order to have a better understanding of what drives productivity, we study the factors associated with a firm's productivity in this section. To do this we use the TFP estimates obtained from the baseline model and aim to identify correlates at the firm level while controlling for sub-sector, country and city fixed effects. The specification is

$$TFP_{i,k,l,j,t} = \alpha_k + \alpha_l + \alpha_j + \alpha_t + X_{i,k,l,j,t}\Gamma + \mu_{i,k,l,j,t} \tag{3}$$

where $TFP_{i,k,l,j,t}$ is the estimated productivity of firm i of sub-sector k located in city l in country j, observed in period t; α_k, α_l, α_j and α_l are the corresponding fixed effects; $X_{i,k,l,j,t}$ is a vector of firm level factors; and $\mu_{i,k,l,j,t}$ is noise. The inclusion of country fixed effects controls for differences in average productivity that are due to time-invariant country characteristics, while city fixed effects deal with time-invariant city characteristics. At the firm level, we explore the following factors: size, age, export status, foreign capital status, access to credit markets and percentage of workers which are unionized. Since in the baseline model the labor factor is not adjusted by the quality of human capital, a control for the education of workers is also included. To simplify the analysis results are reported for the pooled sample of countries. Results are shown in Table 5 in the appendix.

Findings are as follow. First, sub-sector fixed effects alone explain 4 percent of the differences in productivity across firms in the pooled sample and country (similarly to city) fixed effects explain 40 percent, while firm-level characteristics alone explain 15 percent of the variation (see Columns 1, 2, 3 and 5, respectively). Taken together (Column 6) up to 46 percent of the variation in productivity levels is explained by the aforementioned factors. In other words, the results suggest that differences in productivity are to a large extend determined by the characteristics of the geographical area where the city is located. This is an important finding, since it means that a significant part of the productivity of a firm is determined by factors that are partially out of its control.

Second, the sign of the correlations between productivity and firm-level characteristics is as expected. Looking at the results from Column 6 –the estimation with all the possible controls–, keeping other factors constant, larger, older firms, firms with a high proportion of foreign capital and export firms have higher productivity levels. Similarly, firms that have a credit line with a financial institution also report higher productivity levels compared to those that do not. Third, the union status of workers is not significantly correlated to productivity –once other factors are accounted for.

Table 6 is a robustness check where the TFP is measured from a three-factor model (capital, skilled labour and unskilled labour) instead of a two-factor model (capital and labour). While there a few differences in terms of the magnitude of the coefficients –and a loss of statistical significance of the educational variable, as expected–, results in general remain unchanged.

5 Conclusion

We have shown that in the group of Latin American countries examined, the manufacturing sector remains labor intensive, while the heterogeneity in elasticities observed is considerable. While the exact ranking of TFPs in each country was found to be sensitive to the model specifications used, a pattern emerged with Argentina and Chile depicting the highest average TFP, and Bolivia remaining at the bottom of the distribution. Differences in average TFP between Chile and Argentina and the other countries studied were found to be statistically significant. On the other hand, we found that all countries with an intermediate level of average TFP possess some companies, whose productivity level is at least as high as the level of productivity of an average company in the best performing countries. Labor productivity, defined as the value added per full-time employee, was found to be less heterogeneous across countries than TFP, however confirming the results provided in the first part of the study in terms of countries' relative position.

Finally, our results suggest that it is largely country-level rather than firm-level characteristics which drive differences in productivity across firms. In other words, a large share of productivity performance is determined by factors that are not controlled by the firm.

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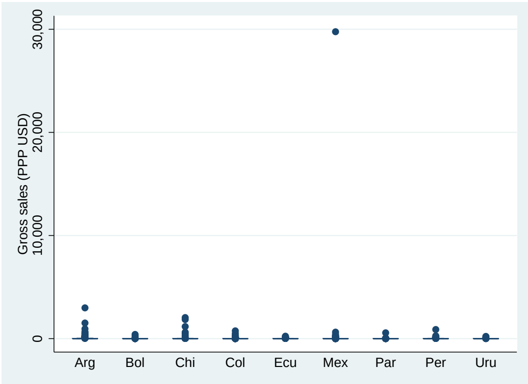
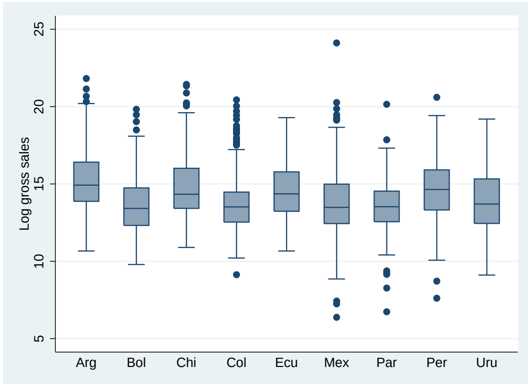
A Supplementary figures and tables

Figure 7: Descriptive statistics

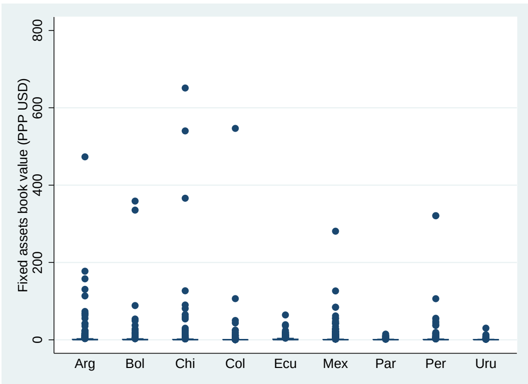
a1. Gross Sales



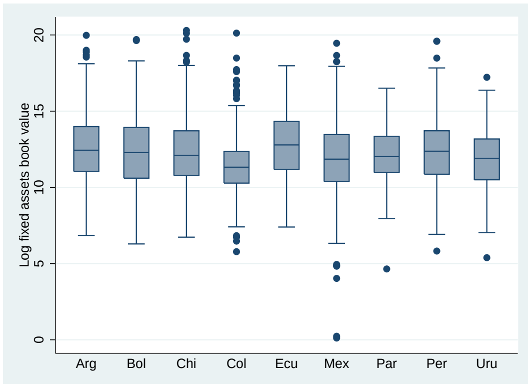
a2. Log Gross Sales



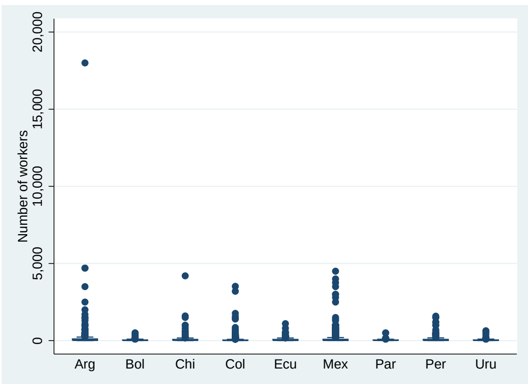
b1. Fixed Assets



b2. Log Fixed Assets



c1. Number of
Full-time Workers



c2. Log of Number of
Full-time Workers

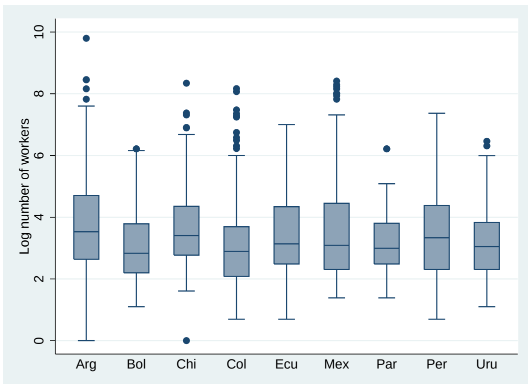


Table 4: Factor Elasticities - Two-period Panel

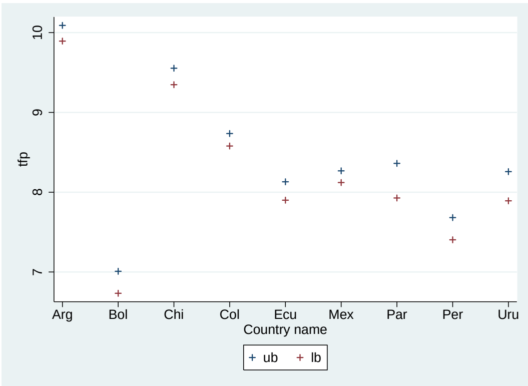
Country	Assets as capital		Energy as capital	
	Pooled OLS	FE	Pooled OLS	FE
	(1)	(2)	(3)	(4)
	α_k	α_k	α_k	α_k
Argentina	0.19	0.03	0.27	0.24
Chile	0.20	0.02	0.22	0.24
Colombia	0.21	0.13	0.28	0.03
Peru	0.23	0.06	0.37	0.21

Figure 8: Comparing different specifications: average TFP confidence interval by country (country-specific factor elasticities)

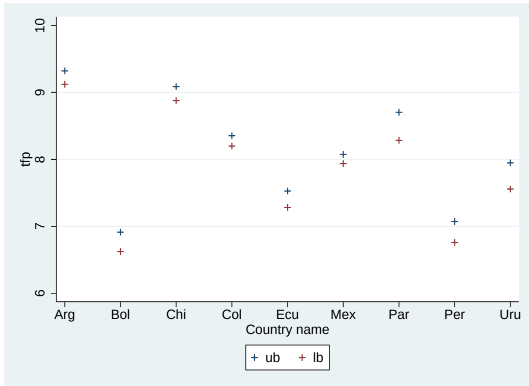
Factors: Capital and Labour

a1. Output: Gross Sales

Baseline

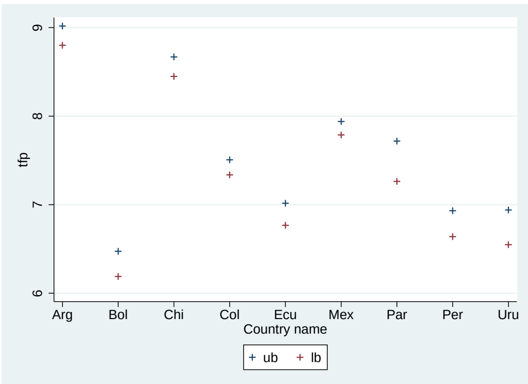


a2. Output: Added Value

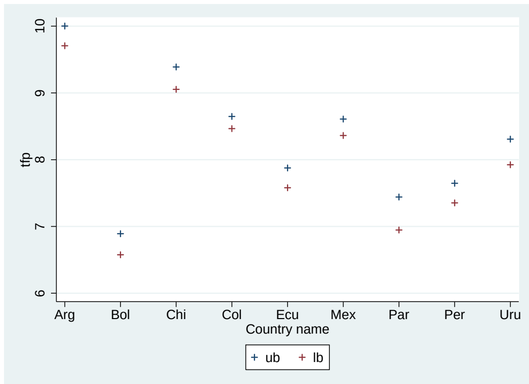


Factors: Capital and Labour Adjusted by Education

b1. Output: Gross Sales

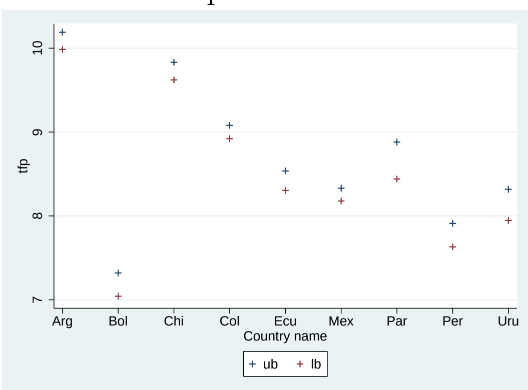


b2. Output: Added Value

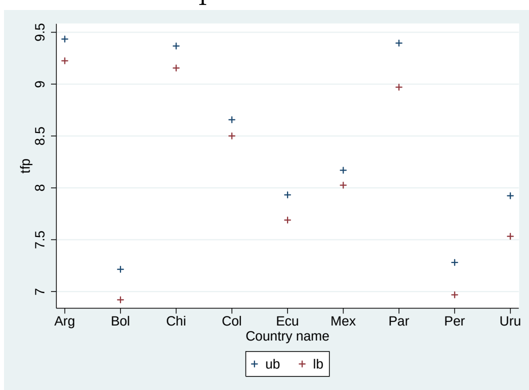


Factors: Capital, Skilled and Unskilled Workers

c1. Output: Gross Sales



c2. Output: Added Value

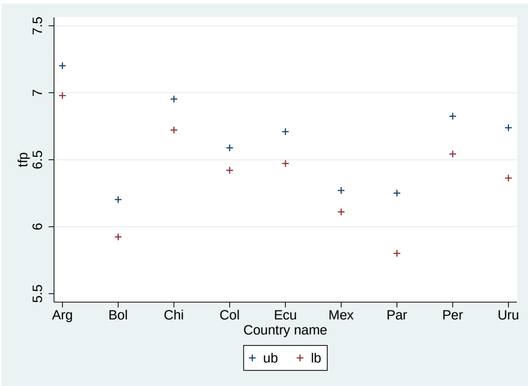


Note: Markers denote the confidence interval in which the average TFP of each country sample is located at the 95% level.

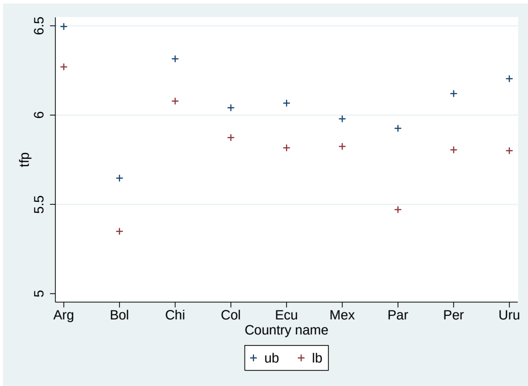
Figure 9: Comparing different specifications: average TFP confidence interval by country (factor elasticities constant across countries)

Factors: Capital and Labour

a1. Output: Gross Sales

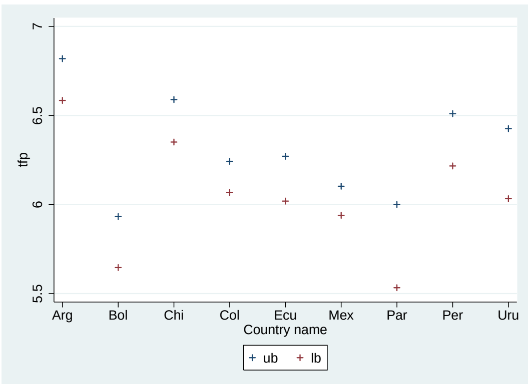


a2. Output: Added Value

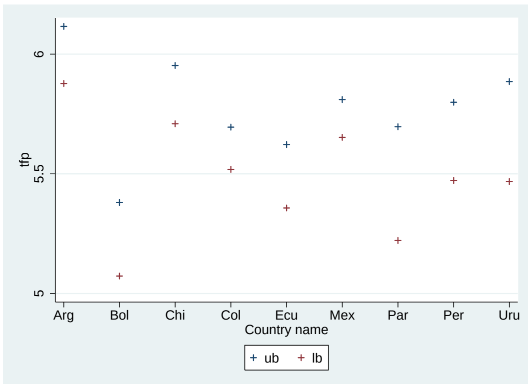


Factors: Capital and Labour Adjusted by Education

b1. Output: Gross Sales

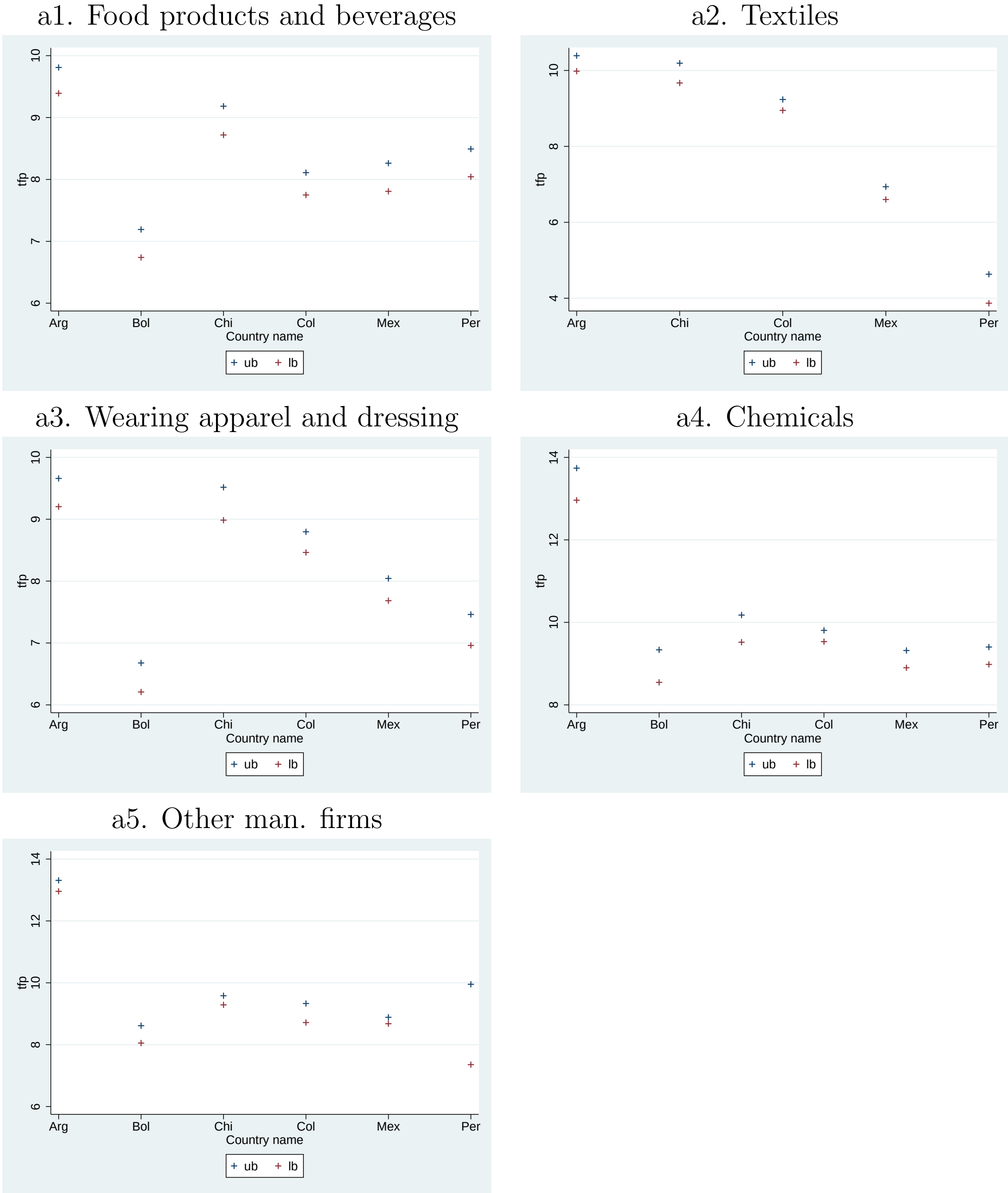


b2. Output: Added Value



Note: Markers denote the confidence interval in which the average TFP of each country sample is located at the 95% level.

Figure 10: Sub-sectors: average TFP confidence interval by country, baseline model



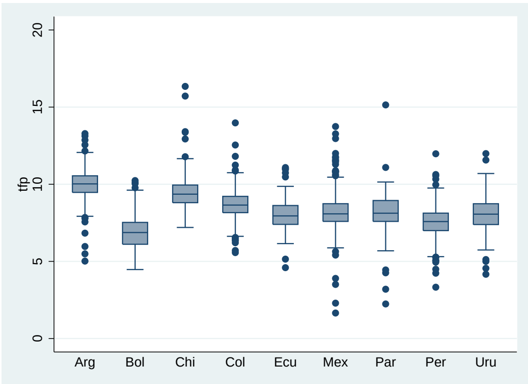
Note: Markers denote the confidence interval in which the average TFP of each country sample is located at the 95% level.

Figure 11: Comparing different specifications: TFP distribution by country

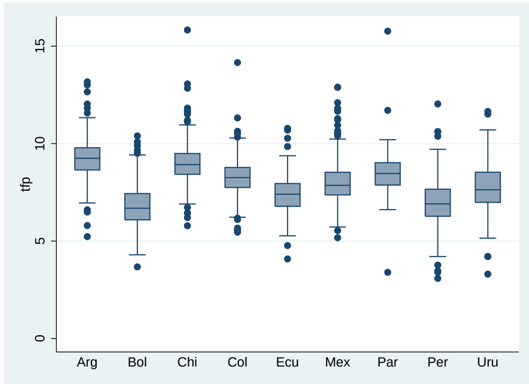
Factors: Capital and Labour

a1. Output: Gross Sales

Baseline

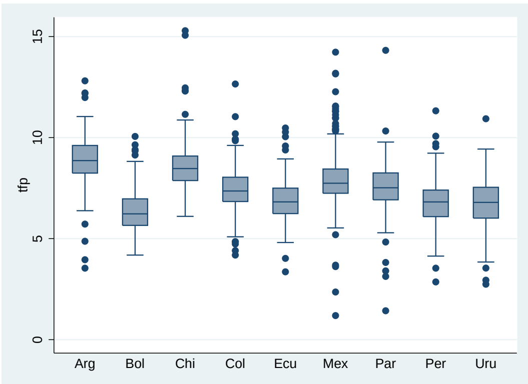


a2. Output: Added Value

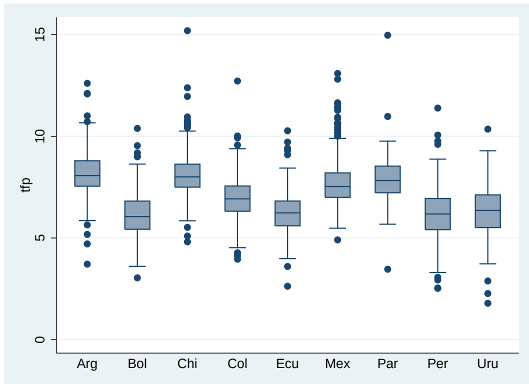


Factors: Capital and Labour Adjusted by Education

b1. Output: Gross Sales

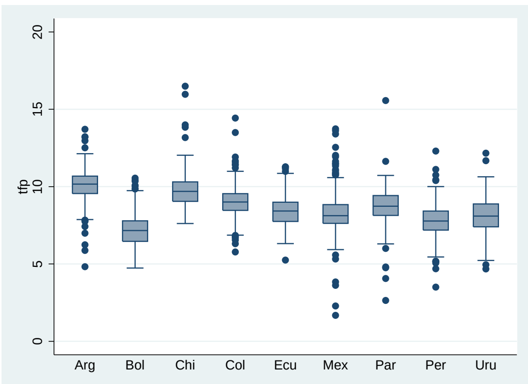


b2. Output: Added Value



Factors: Capital, Skilled and Unskilled Workers

c1. Output: Gross Sales



c2. Output: Added Value

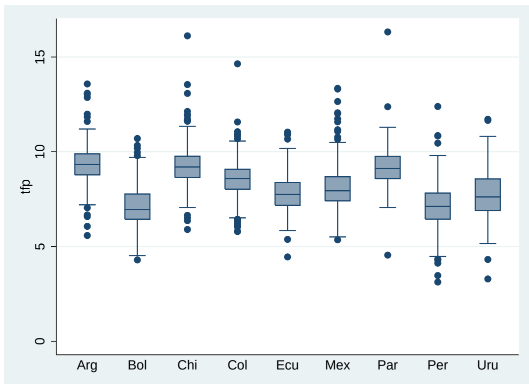
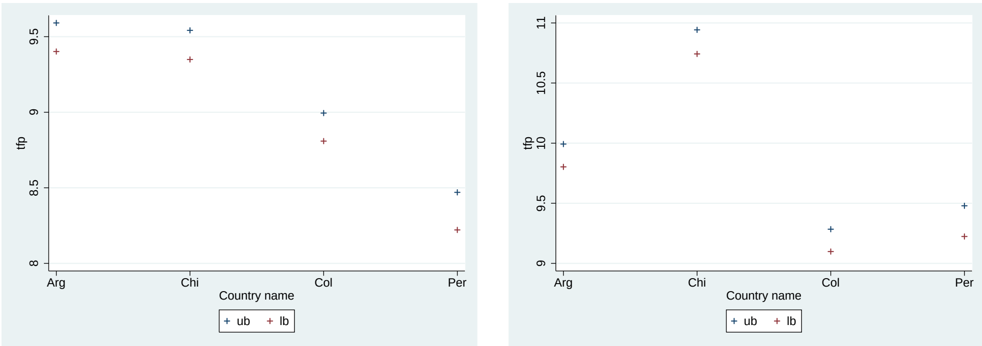


Figure 12: Panel results: average TFP confidence interval by country
a. Pooled OLS (energy as capital) b. Fixed Effects (energy as capital)



Note: Markers denote the confidence interval in which the average TFP of each country sample is located at the 95% level.

Table 5: Baseline specification: correlates of TFP, pooled sample

	(1)	(2)	(3)	(4)	(5)	(6)
Firm has between 20 and 99 emp.					0.15	0.137
					(0.089)*	(0.045)***
Firm has more than 99 emp.					0.1	0.217
					(0.126)	(0.06)***
Above 50 per cent owned by foreign capital					0.186	0.504
					(0.122)	(0.093)***
Firm exports					0.233	0.245
					(0.146)	(0.043)***
Firm exports and has foreign capital					0.155	-.185
					(0.209)	(0.142)
Age of the firm					0.007	0.002
					(0.001)***	(0.001)*
Firm has a credit line or a loan					0.308	0.193
					(0.124)**	(0.074)***
Average production worker has secondary degree or more					0.39	0.164
					(0.19)**	(0.051)***
% of workforce unionized					0.009	0.00005
					(0.005)*	(0.0004)
Obs.	3177	3177	3177	3177	3101	3101
R^2 adjusted	0.042	0.402	0.407	0.428	0.148	0.462
City fixed effects	No	No	Yes	Yes	No	Yes
Country fixed effects	No	Yes	No	Yes	No	Yes
Sub-sectors fixed effects	Yes	No	No	Yes	No	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: Robustness check: correlates of TFP, pooled sample

	Baseline model	3 Factors model
	(1)	(2)
Firm has between 20 and 99 emp.	0.137	0.22
	(0.045)***	(0.041)***
Firm has more than 99 emp.	0.217	0.352
	(0.06)***	(0.056)***
Above 50 per cent owned by foreign capital	0.504	0.517
	(0.093)***	(0.094)***
Firm exports	0.245	0.244
	(0.043)***	(0.042)***
Firm exports and has foreign capital	-.185	-.202
	(0.142)	(0.139)
Age of the firm	0.002	0.002
	(0.001)*	(0.001)
Firm has a credit line or a loan	0.193	0.206
	(0.074)***	(0.069)***
Average production worker has secondary degree or more	0.164	0.084
	(0.051)***	(0.063)
% of workforce unionized	0.00005	0.0002
	(0.0004)	(0.0005)
Obs.	3101	3086
R^2 adjusted	0.462	0.453
City fixed effects	Yes	Yes
Country fixed effects	Yes	Yes
Sub-sectors fixed effects	Yes	Yes
Year fixed effects	Yes	Yes

The baseline model is also presented in Table 5, Column (6). The model with 3 factors has as factors capital, number of skilled workers and number of unskilled workers.