Decomposing firm-level productivity growth and assessing its determinants: evidence from the Americas

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Abstract

This paper provides novel empirical evidence on productivity growth in the manufacturing sector in Chile, Colombia, Mexico and Peru. Relying on plant-level data, we first decompose productivity and productivity growth into plant-level growth and market allocation forces. While the average productivity of the survivors is higher than the overall contribution of reallocation forces, during recessions the inverse is true and reallocation gives a positive, albeit small, contribution to aggregate productivity growth. Next we analyze how policy measures can determine allocative efficiency levels and growth, and find important scope for action on education, financial regulation, and structural reforms.

Keywords Plant-level · Productivity · Decompositions · Regulation · Growth

JEL Classification D22 · L5 · O47

1 Introduction

A broad consensus in economics attributes cross-country differences in income per capita to a large extent to differences in aggregate productivity and past productivity growth. In turn, aggregate productivity depends on the performance of firms and their capacity to

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adopt technology and innovate, as well as on the performance of markets and their efficiency in allocating resource across firms (e.g. Bartelsman et al. 2013).¹ In the presence of distortions that impede an efficient allocation of resources across firms and the process of entry and exit of firms, more productive units may fail to grow, thus reducing aggregate productivity. Recent empirical literature has highlighted the high degree of cross-sectional heterogeneity in productivity even within narrowly defined sectors (Syverson 2008), and attributed it to the misallocation of resources across firms (e.g. Hsieh and Klenow 2009).

This paper investigates both channels of aggregate productivity growth using firm-level data from the manufacturing sector in four Latin American countries (Chile, Colombia, Mexico and Peru) during the past decade, and assesses which regulatory and policy measures are correlated with them. The first part of the analysis decomposes manufacturing aggregate productivity and aggregate productivity growth at the industry level using Olley and Pakes (1996) and Dynamic Olley–Pakes (Melitz and Polanec 2015) techniques. We accessed plant level microdata from these four countries separately² and analyzed them based on an harmonized methodology, thus providing a first comparative descriptive analysis for these four countries jointly. We infer the extent of resource allocative efficiency from the covariance of market shares and productivity, as introduced by Olley and Pakes (1996), where larger positive values indicate that more productive firms use higher shares of industry inputs. In a similar way, the Dynamic Olley–Pakes decomposes industry productivity *growth* between the change in the average productivity of surviving firms, and a reallocation term which distinguishes the contribution of entrants, exiters, and the covariance of size and productivity of survivors to productivity growth. Such a decomposition provides a more accurate picture of the process of creative destruction in the economy by distinguishing between survivors, entrants and exiters.

We find that the allocation of resources (i.e. employment) across establishments improved in the aggregate manufacturing sector during the 2000s, but that this aggregate picture hides notable heterogeneity across industries and even more across firms. Allocative efficiency is found to be relatively less important than average-firm productivity in shaping aggregate productivity growth (explaining between 15 and 37% of total manufacturing aggregate productivity across all years and countries). The dynamic decomposition highlights that the main component of year-on-year productivity growth remains the change in average productivity of the survivors, both in boom and crisis periods. However, when manufacturing productivity is decreasing in the aggregate, the reallocation contributions are usually positive, albeit small, and mostly driven by the change in the covariance of market shares and productivity of the survivors. We also find evidence of a small but positive contribution of exiters to productivity growth in years of negative aggregate productivity growth, except for Mexico and Colombia during the Great Recession, where more productive establishments also exited. Overall, our results suggest that crises have so far represented an opportunity to restructure production in the manufacturing sector in the countries considered.

The second part of this paper investigates which policy levers can be activated to improve allocative efficiency and the contribution of reallocation to aggregate productivity growth. If differences in regulations affect the product, labor, skills or credit markets, they

¹ We use the term firm or establishment interchangeably even if our empirical analysis will rely on establishment-level information.

² This was driven by confidentiality restrictions imposed by the various countries for accessing firm-level data.

can also impact the extent to which inputs of production are efficiently allocated across firms in the overall manufacturing sector. In order to minimize concerns about endogeneity, we rely on a difference-in-difference approach that builds on the original paper by Rajan and Zingales (1998), and we estimate the impact of different policy variables comparing industries which have different level of exposure (or dependence) to a specific policy. We thus assume that firms operating in industries which are more exposed (or dependent) to a certain policy are disproportionately more affected by changes in that policy.

Our results confirm that changes in framework conditions play an important role in shaping allocative efficiency across industries, as a result of the industries' differential exposures to regulatory and policy changes. While labor market and infrastructure policies have a positive but marginal impact on allocative efficiency in industries which are characterized by high capital intensity and trade penetration, product market reforms can be leveraged to improve allocative efficiency especially in sectors displaying relatively low product sophistication. Longer insolvency procedures worsen resource allocation in sectors which rely more heavily on external finance, possibly because of a more challenging environment for firm entry or for the development of productive firms which rely on external finance. The same holds true for allocation in sectors characterized by high product complexity or, to a certain extent, high managerial capabilities. More complex productions indeed are likely to require more advanced institutional settings to ensure the enforcement of contracts and the protection of investors' rights.

To our knowledge, this is the first time such a productivity analysis is carried out for these Latin American countries in a comparable manner, exploiting a uniform methodology applied to comparable firm-level data. We contribute to the existing literature by extending the set of policies (education, infrastructure, product, labor and credit market) and industry characteristics (capital and skill intensity, product complexity, managerial capabilities, financial dependence, trade exposure) which are taken in consideration to explain the dynamics of allocative efficiency. Furthermore, we investigate the policy determinants of the outcomes of both a static and a dynamic productivity decomposition, and highlight the different conclusions one can draw from them. This in turn can inform the present debate on the causes of the productivity slowdown in OECD countries (e.g. Fernald 2015; Byrne et al. 2016; Syverson 2017): differences across countries and the time evolution of productivity do not only originate from slow adoption of less advanced technology by firms, but also from how resources flow across firms with heterogeneous productivity.

The paper consists of seven main sections. The first one relates our analysis to previous studies of relevance for the investigation. The next two sections present the data at hand, the productivity decompositions we use and the reasons for choosing them, and the results of the decompositions themselves. This is followed by the discussion of our estimation strategy and the results of the econometric analysis, and by the conclusion. The appendixes provide further details on the data construction, both for the micro-level datasets (Appendix 1) and the country and industry data (Appendix 2).

2 Literature

Aggregate total factor productivity growth is normally estimated as the part of GDP growth that cannot be explained by the growth in the inputs of production (employment, physical capital, and human capital). This unexplained component measures the country's efficiency in the use of inputs for producing one unit of output. Recent analyses, by contrast, have

investigated aggregate productivity as the result of firm-level processes, where firms are assumed to be heterogeneous in their productivity even within narrowly defined sectors (Syverson 2004; Bartelsman et al. 2004, 2009; Foster et al. 2008). This heterogeneity in firm-level productivity can reflect misallocation of resources across firms: as low-productivity firms have lower survival than high-productivity firms, aggregate (industry) productivity can improve by reallocating resources among incumbents with different productivity levels, or between incumbents and firms entering or exiting the market. For a recent survey of this literature, see Restuccia and Rogerson (2013). Cross-country differences in output per capita can be at least partially explained by this misallocation of resources (Banerjee and Duflo 2005; Restuccia and Rogerson 2008; Hsieh and Klenow 2009).

The availability of micro-level data allows investigating the extent of such differences in the link between misallocation and productivity at the cross-country level. Bartelsman et al. (2004, 2013) analyze the results of productivity decompositions both in levels and in growth for European, Latin American and East Asian countries. They find important heterogeneity of countries and sectors in allocative efficiency for the manufacturing sector, but show that this component of aggregate productivity growth was on average smaller than the average firm productivity term, and often negative. In this article, we apply a decomposition to labor productivity (growth) for Chile, Colombia, Mexico and Peru. Our data deliver the stylized facts described above, i.e. the wide heterogeneity in manufacturing allocative efficiency across countries, and its smaller importance relative to average firm productivity. Aside for providing first-time decompositions for some of the considered countries, we pay special attention to differences across manufacturing industries, and relate it to the different technological paths of industries.

This static decomposition, however, does not distinguish between reallocation among incumbents and reallocation caused by churning (that is, the entry and exit of firms). By neglecting that entrants and exiters can have substantially different productivity than incumbents and by bundling these firms together, the Olley and Pakes (1996) decomposition understates the importance of creative destruction in the market. To overcome this limitation the literature has proposed several decompositions, usually breaking down productivity growth into four components: growth in productivity of the incumbents, changes in market shares of the incumbents, contribution of entrants, and contribution of exiters (Baily et al. 1992; Griliches and Regev 1995; Foster et al. 2001).

In our analysis we rely on the dynamic decomposition proposed by Melitz and Polanec (2015), which is an extension of the Olley–Pakes static decomposition taking into account entry and exit. This allows for neater comparisons between static and dynamic decompositions. Furthermore, Melitz and Polanec show that previously-proposed dynamic decompositions suffer from biases by construction, and fail to account appropriately for the contribution of entry and exit in aggregate productivity. Although the sign of such bias is theoretically ambiguous, the authors show that previous decompositions underestimate the role of survivors and overestimate that of entrants in the aggregate productivity of fast growing economies. This decomposition has been recently applied by Harrison et al. (2013) and Decker et al. (2017), despite the possible shortcomings highlighted in Petrin and Levinsohn (2012—see later paragraphs).

The second part of this study investigates the role selected policy instruments play in shaping aggregate labor productivity (growth) through reallocation. Restuccia and Rogerson (2013) review the literature on misallocation and point at the existence of two analytical approaches: the “direct” approach chooses one or more policy, regulatory or institutional aspects in the economy and assesses the extent to which they impact allocation and productivity. The “indirect” approach instead does not highlight which factors can cause misallocation, but rather bundles them as “wedges” in the first order condition

of the firms' profit maximisation problem, and can deliver a quantitative assessment of how these wedges produce misallocation (e.g. Restuccia and Rogerson 2008; Hsieh and Klenow 2009). While both approaches have shortcomings (ref. Restuccia and Rogerson 2013), we follow a "direct" approach in this paper, as it is more suitable to assess the relative importance of clearly identified regulatory measures for changes in allocative efficiency and aggregate productivity. This approach can therefore inform policy makers about possible instruments to be leveraged to increase productivity growth. Furthermore, the "indirect" approach requires measuring productivity as total factor productivity only, which is bound to be measured with error in our context. Finally, Haltiwanger et al. (2018) show that the fundamental tenet of the "indirect" measure, i.e. that dispersion in firm total factor productivity (TFPR) signals the existence of distortions in the allocation of inputs across firms, only holds under special and restrictive shapes of demand and supply functions. When these assumptions are not met, the indirect approach (at least as specified in Hsieh and Klenow 2009) can identify producers as inefficient even when their input mix is efficient.

Our paper can therefore benefit from a number of previous studies which have analyzed the role of policies in determining firm level dynamics or productivity dynamics more precisely. We give a more extensive recount of these studies in the section detailing the results of our econometric estimation. The work of Andrews and Cingano's (2014) is perhaps most closely related to ours, as it investigates the role of regulatory and policy measures in aggregate productivity dynamics. The authors show econometrically how selected regulatory measures (employment protection legislation, bankruptcy legislation, product market regulation) can lower allocative efficiency. Compared to the present study, however, they focus on OECD countries rather than Latin American ones, take in consideration a smaller range of policies, and only make use of a static productivity decomposition. A previous study by Pages et al. (2009) uses the same data as Bartelsman et al. (2004) to analyze productivity in Argentina, Colombia and Chile in the 1980s in particular. They show that the correlation between the allocative efficiency and average productivity terms in Latin American countries was much lower than in other countries, thus suggesting that the contestability of the market produced by firm entry and exit in the manufacturing sectors was not affecting the productivity of the survivors. Their analysis of the relationship between policies and firm growth, entry or exit, however, is insightful but purely descriptive.

3 Data

3.1 Manufacturing surveys

This study focuses on the analysis of productivity growth in Chile, Colombia, Mexico and Peru, using establishment-level data from the manufacturing sector.³ For Mexico, we rely on an unbalanced, establishment-level panel data set for the years 2003–2011, the Annual Industrial Survey (EIA). The survey excludes establishments with fewer than 15

³ Only information on manufacturing firms is available. Furthermore, the Mexican dataset makes it impossible to distinguish between single-product and multi-product firms. It is thus assumed that the observed establishments operate in a single sector.

employees, with a target coverage of at least 85% of sales in the manufacturing sector.⁴ For Colombia, plant-level information for the years 2000–2011 was obtained from the Manufacturing Survey (EAM), which covers the universe of manufacturing establishments with at least ten employees or at least Col\$136.4 million in revenues from sales.⁵ The Chilean data are based on the national annual manufacturing survey (Encuesta Nacional Industrial Anual, ENIA), a census of all manufacturing plants with at least ten individuals in the labor force. Even though at the time of writing the ENIA is available until 2010, confidentiality constraints limit the coverage to the 1995–2007 period for this study.⁶ The analysis for Peru is based on firm-level data from the Annual Economic Survey (EEA) for 2007–2012. The survey is representative of formal firms in agriculture, manufacturing, trade and services in all departments and aims to cover at least 70% of output (sales) in each sector. The present analysis is restricted to the manufacturing sector, to increase homogeneity with the other considered countries. The sample, designed on the basis of tax administration data (SUNAT), always includes listed firms and firms reported in the Census stratum. Non-census firms are randomly sampled following a single-stage stratification.⁷

The samples differ across country in the way entry and exit are identified. Plants were selected into the sample for the census year (2003) for Mexico and on a yearly basis for Colombia, then followed over time. For Mexico, while this process allows us to construct a plant-level panel, it also implies that the sample allows for limited entry in non-census years (usually when new plants are especially relevant in size). In Colombia, DANE revised the sample on the basis of other sources of information in 2008.⁸ However, exit is reported consistently in both cases. For Peru, the inverse is true: as firms report their first year of operation, firm's entry can be determined, but exit is not reported in the data reliably, as some firms exit just because they are not included in the follow-up sample. For Chile, entry is defined based on the first year in which any particular plant is registered in the sample, while exit is recorded based on the last year in which a plant appears in the sample. However, firms may exit from the sample, because they fall below the minimum size threshold for inclusion. For both Peru and Chile, as a consequence, exit from the sample could reflect firms' output falling below a certain threshold as well as real exit.

In order to make our datasets comparable across country, we converted the country-specific industrial classification into an ad-hoc industrial classification most similar to ISIC rev. 3.1.⁹ The resulting sample (after cleaning) contains 4915 plants in 1995 and 4472 in

⁴ These statistics are for 2005. In 2009 the survey covers 90% of manufacturing sales in Mexico. The difference is attributable to Maquilladoras, which are excluded from our dataset. After cleaning (see Appendix 1) our dataset contains 70% of total value added in the manufacturing sector in 2009.

⁵ This is the threshold for 2012, and it changes yearly on the basis of the producer price index.

⁶ Many studies have used this plant level dataset for research purposes (e.g. Pavcnik 2002; Levinsohn and Petrin 2003). The sample covers the quasi-totality of value added in the manufacturing sector as a whole. Even though the information is at the plant level, more than 95% of the plants produced for single-plant firms in 1996, the only year displaying both firm and plant level information.

⁷ In 2011 the stratification methodology and the output threshold for firms to be included in the census changed, translating into a decrease in the sample size and in particular in the number of large firms included in the sample. For this reason the dynamic decompositions and econometric analysis below will be restricted to the years 2007–2010.

⁸ Until 2007, the EAM was updated on the basis of mini-surveys that were conducted by DANE's regional offices; starting in 2008, the central DANE cross referenced its sample with other sources of information (Superintendence of Companies, Chambers of Commerce, Free Export Zones, and the exporter's database).

⁹ To be able to compare Colombian, Mexican, and U.S. data in the descriptive statistics, we constructed a conversion table between the SCIAN/NAICS 2002 and ISIC 3.1 classifications. This is discussed in greater detail in the data appendix.

2007 for Chile, and 6925 plants in 2000 and 8988 in 2011 for Colombia. For Mexico, the sample size decreases from 5782 plants in 2003 to 4499 in 2011, and from 2465 firms in 2007 to 1969 firms in 2012 in the case of Peru.

These surveys provide information on all inputs of production and sources of revenues. It is therefore possible to compute labor productivity or value added per worker, where value added is computed as revenues from sales minus the cost of all intermediate inputs and electricity. Based on information on capital stocks at book value and investments we construct a measure of investment in technology (or net investment in capital equipment represented by machineries). All variables are deflated with the most disaggregated deflator at our disposal, then transformed into U.S. dollars.¹⁰ Further details on the construction of the capital variable, deflation, and the conversion of national industrial classifications into a derivation of ISIC3.1 are provided in Appendix 1.

Table 1 reports basic statistics based on the pooled sample for Chile, Colombia, Mexico, and Peru. It highlights significant differences in the types of establishments surveyed. While the Mexican and Peruvian samples cover relatively large plants, respectively with 220 and 139 employees and US\$31.5 and 10.5 million in revenues per year on average, plants in the Chilean and Colombian data set are significantly smaller on average, especially as far as employment is concerned (approx. 70 employees and US\$5–10 million). The average plants in Chile and Mexico are similar in labor productivity, and twice as productive as the average plants or firms in Colombia and Peru. The within-country heterogeneity in productivity is also high, with low-productivity plants (5th percentile) producing 4.5 thousand US\$ per employee in Mexico (US\$3.6 and 4 thousand for Colombia and Chile) versus a minimum of almost US\$400 thousand in high-productivity plants at the 99th percentile for Chile and Mexico (US\$163 thousand for Colombia).

3.2 Country- and industry-level data

The second part of this analysis exploits industry-level information from the U.S. and country-level information from the Latin American countries of interest, in order to assess how selected policy determinants shape allocative efficiency (the “between” term in our decomposition). The complete list of data sources and definitions is reported in the Data Appendix 2.

First, we use three indicators to capture the degree of financial development in Latin American countries: accounting practices, the level of independence of the banking

¹⁰ The absence of firm- or plant-specific prices affects the measurement of real output, intermediate consumption, and value added. As described in the Appendix 1, we follow a standard strategy in the literature, and deflate firm-level observables with industry-level price indexes. Real value added can therefore be written as:

$$VA_{ijt} = \frac{P_{ijt}^q Q_{ijt}}{P_{jt}^q} - \frac{P_{ijt}^m M_{ijt}}{P_{jt}^m}$$

where firm i operates in sector j at time t , and P^q and P^m are, respectively, the price charged for one unit of output and paid for one unit of intermediate material inputs. If firm i sells at prices lower than the industry ones, real output is estimated to be lower than it actually is. Similarly, if industry-level prices rose faster than firm-specific ones, the firm’s output growth will be underestimated. The same holds true for material inputs. The bias in the measurement of real value added and labor productivity (growth) will ultimately depend on the correlation between (changes in) price levels of materials and output and their deviation between industry- and firm-level.

Table 1 Sample description

	Count	Mean	SD	p5	p99
Chile					
Sales	58,524	9980	85,364	124	135,515
Employment	58,524	67	134	7	657
Capital	58,524	4028	64,380	0	54,247
Value added	58,524	4601	39,855	47	62,282
Value added/employment	58,524	49.40	568.25	3.98	394.51
Colombia					
Sales	84,815	5207	55,208	74	68,030
Employment	84,815	70	153	5	713
Capital	82,050	2396	20,787	9	40,375
Value added	84,815	2523	31,005	35	33,567
Value added/employment	84,815	22.94	74.25	3.58	162.88
Mexico					
Sales	47,868	31,626	183,192	193	333,675
Employment	47,868	221	389	10	1936
Capital	47,868	11,648	71,296	30	163,975
Value added	47,868	15,019	76,334	84	179,814
Value added/employment	47,868	45.28	83.46	4.51	394.68
Peru					
Sales	10,284	10,657	36,601	320	156,840
Employment	10,284	139	368	5	1653
Capital	10,247	5359	33,028	11	92,483
Value added	10,284	3231	12,128	56	49,910
Value added/employment	10,284	21.46	22.90	4.72	119.94

Sales, capital and value added are reported in thousand deflated US\$. The statistics are reported for the cleaned sample, covering the years 1995–2007 for Chile, 2000–2011 for Colombia, 2003–2011 for Mexico, and 2007–2012 for Peru

supervisory authority from court intervention, and the years needed to resolve an insolvency (Barth et al. 2012 and World Bank Doing Business Database). Second, we use years of schooling from UNESCO to capture education. Unfortunately, this is collected with less frequency than other country-year variables (as it also changes more slowly). Lastly, we use indicators of infrastructure (port) efficiency, labor market stringency (in the form of cost of laying off workers) and structural reforms, as developed by Lora (2012) and Sarriera et al. (2013).

Industry-level information from the U.S. is used to proxy the “natural” exposure of a sector to a given set of policies, in line with the framework developed by Rajan and Zingales (1998). Industry-level information for the United States refers to the 2-digit ISIC3 sector for the year 1999 or earlier (in case 1999 is missing), where a year preceding our sample was chosen to increase the exogeneity of the industry-level regressor. Industry-level data are accessed from national account industry-level databases (OECD Structural Analysis Database) or aggregated from firm level sources (ORBIS) and individual-level surveys (U.S. Current Population Survey). Other indicators of interest were derived from previous studies. In particular, a measure of relationship specificity of inputs is sourced from Nunn

(2007) and one for the share of traded value added which is transported by sea (to capture the reliance on transport infrastructure of firms in the industry) is obtained from Cristea et al. (2013). A measure of investment in organisational capital in the industry from Le Mouel et al. (2016) is estimated on the basis of industry employment and the salaries of workers employed in organisational-intensive tasks. Lastly, industry measures of financial dependence rely on information on the composition of firms' balance sheets. Rajan and Zingales (1998) approximate the degree of dependence of the company on external funds with the fraction of capital expenditures that a company is not able to finance with internal funds. The ability of an industry to provide collaterals is measured using firm-accounting data from Orbis.

4 Productivity decomposition

4.1 Static decomposition

Tracking a static decomposition of aggregate (industry) productivity over time can inform about the extent to which productivity growth is driven by the change in average firm productivity (the “within” firm component) or the reallocation toward more productive plants (the change in the “between” firm component). One approach to decomposing aggregate productivity was originally proposed by Olley and Pakes (1996).¹¹

Following Olley and Pakes (1996), we first define the aggregate labor productivity of industry j at time t Ω_{jt} , as the weighted average of firm-level labor productivity, where weights are calculated as the share of firm employment in total industry employment.¹² Aggregate industry productivity can then be decomposed into unweighted mean productivity, $\bar{\omega}_{jt} = \frac{1}{n_{jt}} \sum \omega_{ijt}$, and a term capturing the covariance between firm productivity and firm size $\sum (s_{ijt} - \bar{s}_{jt})(\omega_{ijt} - \bar{\omega}_{jt})$. With $s_{ijt} \geq 0$ representing the weight (that is, the importance) of firm i in industry j , and $\bar{s}_{jt} = \frac{1}{n_{jt}}$, one can write:

$$\Omega_{jt} = \bar{\omega}_{jt} + \sum (s_{ijt} - \bar{s}_{jt})(\omega_{ijt} - \bar{\omega}_{jt}) \quad (1)$$

Aggregate productivity in the industry or economy can grow either because of increases in the average productivity of a firm (“within firm” component) or because the market reallocation increases the size (weight) of more productive plants. For higher covariance values, a larger share of employment in the industry is “allocated” to the most productive plants, resulting in higher aggregate productivity. Given a fixed number of plants with heterogeneous productivity, shifting employment away from low-productivity to high-productivity plants increases aggregate productivity and the covariance between firm efficiency and size.

¹¹ The subscript for the country is omitted to simplify the notation.

¹² An important part of the literature computes this decomposition using output instead of employment weights. It is mostly the case, however, that output weights are used when productivity is estimated as total factor productivity (Bartelsman et al. 2009, 2013). As we are focusing our analysis on labor productivity only, we prefer using employment weights. In our context, the weights measure the extent to which the labor input is allocated across plants.

Fig. 1 Density of industry and firm-level labor productivity growth. *Note* Based on cleaned sample. Labor productivity is measured as deflated value added (in US\$) per employee. All years in the sample

Previous studies have usually described allocative efficiency based on a decomposition of TFP, rather than labor productivity. Foster et al. (2008), however, show that the correlation between TFPQ and labor productivity is 60% in the U.S. during the period 1977–1997, while Bartelsman et al. (2013) show that the lessons learned from an Olley–Pakes decomposition in labor productivity are consistent with those of a TFP decomposition. Labor productivity has been extensively used in the literature relevant for our research question (e.g. Bartelsman et al. 2004; Andrews and Cingano 2014; Decker et al. 2017), and imposes lower constraints in terms of quality of the underlying data, but more importantly it is easier to compare across countries and industries. This is especially true considering that the appropriate measure of aggregate TFP would require input-weights (Van Biesebroeck 2008).¹³ To aggregate firm labor productivity to the industry level, we use labor shares for weights s_{ij} , rather than output shares, which would overestimate both aggregate productivity and the correlation between size and productivity. For the same reason we aggregate the level of firms' labor productivity, rather than its logarithm, which would yield a geometric average instead. We still present selected statistics computed on log-productivity, in light of its frequent use in the literature (e.g. Foster et al.

¹³ It is still true, however, that decomposing labor productivity rather than TFP cannot account for the differences in capital intensity across firms and countries. These may reflect in differences in the intensity of use and in the cost of labor which profit maximizing firms will adjust to, and in differences between LP- and TFP-based measures of allocative efficiency as a consequence.

Fig. 2 Firm-level static decomposition (weighted average of manufacturing industries). *Note* Based on cleaned sample. Labor productivity is measured as deflated value added (in US\$) per employee. The graphs aggregates results of the decompositions at the 2-digit industry level using the industry's employment in total manufacturing employment. All years in the sample

2001; Bartelsman et al. 2013). Lastly, a firm's labor productivity is the ratio of its value-added over employment, rather than output over employment, in order to account for the heterogeneity in use of intermediate materials across firms and sectors.¹⁴

Figure 1 reflects the wide heterogeneity in productivity across firms in these countries, and how firms are more heterogeneous than industries. At the firm level, Fig. 1 reports the ratio between the plant's growth rate in a year, over the median growth rate of all plants in the same four-digit sector. At the industry level, the graph reports the ratio between the median growth rate in the four-digit sector over the median growth rate in the economy. Figure 2 plots the trends in aggregate productivity for the four Latin American countries in consideration, for the aggregate manufacturing sector (left vertical axis), as well as the relative size of the covariance term as a percentage of aggregate productivity (right vertical axis). Both aggregate productivity and covariance for the manufacturing sector are calculated as weighted average of the two-digit sector terms across sectors (productivity Ω_{it} and

¹⁴ Nevertheless, our measure of aggregate productivity remains the result of summing (with weights) plant-level technical efficiencies. Petrin and Levinsohn (2012) show that growth in this measure may substantially differ from aggregate productivity growth calculated as the difference between changes in aggregate final demand and in aggregate expenditure in inputs of production. The implications for aggregate productivity growth and its decomposition are further discussed in the next sessions.

covariance, respectively). The weights are constructed as the share of sector employment in total manufacturing employment. As mentioned, under these conditions, micro-aggregated and aggregate labor productivity exactly correspond. In all countries, the overall manufacturing sector experienced some growth in labor productivity, albeit with different magnitudes and despite dips during the Great Recession. The levels of aggregate productivity also differ across countries, as expected from the heterogeneous degrees of economic development displayed by these countries. In 2007, the year where all countries are included in our sample, the Mexican manufacturing sector is four times as productive as the Peruvian one, and twice as productive as the Chilean or Colombian ones.¹⁵ The trend in aggregate productivity is generally increasing across all countries, although the Peruvian sample is possibly too short and too close to the Great Recession to allow for a confident inference about the trend. Over the last 5 years of the respective samples, aggregate manufacturing productivity growth reached approximately 30–35% in Chile and Mexico and 18–20% in Colombia and Peru.

The role of allocative efficiency in explaining these cross-country differences is not minor: the aggregate covariance of firm size and productivity composes as much as 37% of aggregate productivity in Colombia, 20% in Chile and Mexico, and 15% in Peru.¹⁶ Chile in particular displays years of negative covariance, i.e., years when allocation was worse than one which would result from a random allocation of resources across firms. The role of public policies in explaining the dynamics of reallocation will be explored in the next sections. While the Mexican manufacturing sector displays a general increase in the contribution of allocation of employment across plants to aggregate productivity, the same cannot be said for Colombia, where the last years of the sample suggest a deterioration in the allocative efficiency. No clear pattern is identifiable for Chile or Peru over the covered time period.

Several studies have already pointed out that gaps between weighted and unweighted average productivity—the covariances—can differ in size across country (e.g. Bartelsman et al. 2004, 2013; Arnold et al. 2011a). In Bartelsman et al. (2013), for instance, these magnitudes range from 4% in Slovenia to 30% in France or 50% in the U.S. We find relatively smaller covariances than Bartelsman et al. (2004), who measure them to be approximately 40% for Chile and Colombia and even higher for selected South-East Asian countries. But discrepancies can arise for multiple reasons: the years covered; the length of the period analyzed, with shorter-term decompositions yielding usually a larger contribution of the within-firm average component, like in our analysis (see for instance Foster et al. 2001); the level of industry aggregation; the choice of decomposing labor productivity in logarithm or in levels, and the extent of mismeasurement in the main variables in the analysis (i.e., employment and value added).

Table 2 reports the proportion of 2-digit aggregate productivity attributable to the covariances (or “Olley–Pakes gap”), on average across all industries in the manufacturing sector. These averages weighting sectors equally are lower than the sector-weighted averages presented above, with Chile and Mexico displaying roughly similar means and dispersion. Colombia and Peru, however, display a more erratic behavior, and a higher dispersion

¹⁵ It cannot be excluded that the higher average firm productivity in Mexico is related to the sample composition, which includes relatively bigger firms than in the other countries here analyzed.

¹⁶ We prefer to express the covariance as percentage of aggregate productivity because direct comparisons of their level across sectors could be misleading, due to differences in measurement and sampling across countries (e.g. Bartelsman et al. 2004).

Table 2 Static decomposition of labor productivity in the manufacturing sector: OP covariance of as a % of total 2-digit industry productivity, simple average by country and year

	Chile	Colombia	Mexico	Peru
Covariance of productivity				
First year	0.18	−0.02	0.08	0.00
2007	0.13	0.17	0.16	0.00
Last year	0.13	−0.07	0.17	−0.02
Mean over years	0.14	0.10	0.15	−0.07
SD over years	0.03	0.19	0.03	0.08
Covariance of log (productivity)				
First year	0.11	0.16	0.06	0.02
2007	0.10	0.15	0.09	0.02
Last year	0.10	0.10	0.09	0.04
Mean over years	0.10	0.14	0.08	0.01
SD over years	0.01	0.03	0.01	0.03

Based on the cleaned sample. Labor productivity is measured as deflated value added (in US\$) per employee, and it is computed for the each 2-digit industry in the manufacturing section. The reported mean and standard deviation are computed as unweighted moments of the cross-industry year values. For Chile first and last year in the sample are 1995 and 2007, for Colombia 2000 and 2011, for Mexico 2003 and 2011, and for Peru 2007 and 2012

in OP gaps across industries. The relative size of the OP gaps is even lower when looking at the decomposition of log-labor productivity. This is consistent with aggregate industry productivity being calculated differently and residual outliers weighting less due to the logarithmic transformation.

As firms have different production functions and technologies in different industries, it is expected that heterogeneity in allocative efficiency extends to the sectoral dimension, too. Table 3 displays the average contribution of the OP gap to aggregate productivity by 2-digit industry, as an average across all countries and years in the sample. Paper and Motor Vehicles are the 2-digit manufacturing industries displaying the highest allocative efficiency, apparel and electric equipment the lowest. In the econometric analysis below, we will exploit such heterogeneity to understand the role of time-varying policies, while controlling for all time-invariant industry (and country) specific factors which may affect the allocative efficiency.

4.2 Dynamic decomposition

Furthermore, to assess the robustness of the results, we implement an alternative decomposition for productivity growth rather than for productivity levels. This allows us to better distinguish between the contribution of entry and exit from other elements of aggregate productivity (changes in reallocation among incumbents).¹⁷ Indeed Eq. 1 analyzed

¹⁷ It is indeed the case that, in presence of entry and exit, a change in the static OP covariance may not correspond to a change in allocative efficiency. This happens, for example, when a firm displaying below-mean productivity and below-mean-size exits the market: the covariance term decreases, and the unweighted average productivity increases, but this would not correspond to a “true” reduction in allocative efficiency and increase in within-firm productivity. The proposed dynamic decomposition does not suffer of this caveat.

Table 3 Static decomposition of labor productivity: OP covariance as a % of aggregate industry productivity, by industry, then averaged across countries and years

	Mean	SD
Food and beverages	0.23	0.17
Textiles	− 0.01	0.17
Apparel	− 0.19	0.32
Leather	− 0.04	0.38
Wood	0.08	0.43
Paper	0.31	0.22
Printing	0.23	0.15
Chemicals	0.13	0.16
Rubber and plastics	0.13	0.14
Non-metallic minerals	0.19	0.17
Basic metals	0.14	0.57
Fabricated metals	0.02	0.25
Equipment and electric motors	− 0.08	0.56
Electrical and optical equipment	0.09	0.29
Motor vehicles	0.24	0.47
Furniture and other manufacturing	− 0.02	0.56

Based on the cleaned sample. Only sectors which exist in all four reference countries are displayed, leaving out Tobacco, Oil, Office and Communication, Transport and Medical equipment producers. Labor productivity is measured as deflated value added (in US\$) per employee, and it is computed for each 2-digit industry in the manufacturing section, then averaged over all countries and years

productivity in levels and did not distinguish between entrants, exiters and surviving firms. These types of firms, however, significantly differ from each other in many respects, including size and productivity dynamics. If an entrant firm displays higher productivity than incumbents, it will reduce market shares from them, leading to growth in aggregate industry productivity. That is why we decompose aggregate productivity growth in four components: (1) changes in the average productivity of the incumbents that stay in the market in all years (or “survivors”); (2) changes in market shares among these survivors; (3) the contribution of entrants in the second period; and (4) the contribution of exiting plants. In this manner, we extend the Olley and Pakes (1996) decomposition following Melitz and Polanec (2015), so that:

$$\Delta\Omega_{jt} = \Delta\bar{\omega}_{pjt} + \Delta Cov_{pjt} + \left(\sum_{i \in E} s_{ijt} \right) (\Omega_{Ejt} - \Omega_{pjt}) + \left(\sum_{i \in X} s_{ijt-1} \right) (\Omega_{pjt-1} - \Omega_{Xjt-1}) \quad (2)$$

where subscript p refers to survivors, E to entrants in t , and X to exiters in $t-1$. The first and second terms on the right-hand side measure the contribution of survivors to aggregate (sectoral) productivity growth, which is decomposed according to Olley and Pakes (1996) into a change in average productivity of the survivors between t and $t-1$, and a term for the change in covariance between market share and productivity for the survivors. The contribution of entrants (respectively, exiters) is a function of the share of the firm’s output in total entrants’ (respectively, exiters’) output in the industry, $\sum_{i \in E} s_{ijt}$ and $\sum_{i \in X} s_{ijt-1}$, and the difference between aggregate productivity of entrants (respectively, exiters) and that of survivors: $(\Omega_{Ejt} - \Omega_{pjt})$ and $(\Omega_{pjt-1} - \Omega_{Xjt-1})$.

Table 4 Dynamic decomposition of labor productivity in the manufacturing sector: unweighted averages of 2-digit industry values by country and year

	Chile	Colombia	Mexico	Peru
Unweighted productivity				
First year	0.06	−0.08	0.04	0.11
Last year	−0.05	0.07	0.08	0.07
Mean over years	0.00	0.01	0.03	0.03
SD over years	0.03	0.10	0.08	0.15
Reallocation				
First year	0.00	0.06	0.03	−0.01
Last year	0.05	0.04	0.02	0.00
Mean over years	0.02	0.01	0.02	−0.00
SD over years	0.03	0.02	0.02	0.03
Entry				
First year	−0.01	0.01	0.00	0.01
Last year	0.01	0.00	0.00	−0.02
Mean over years	0.00	0.00	0.01	−0.01
SD over years	0.01	0.01	0.02	0.02
Exit				
First year	−0.01	0.01	0.00	0.02
Last year	0.02	0.01	0.00	0.00
Mean over years	0.01	0.00	0.00	0.02
SD over years	0.02	0.01	0.02	0.02

Based on the cleaned sample. Labor productivity is measured as deflated value added (in US\$) per employee, and it is computed for each 2-digit industry in the manufacturing section. The reported mean and standard deviation are computed as unweighted moments of industry-year values. “Reallocation” is the sum of the contribution of entrants, exiters and the change in the covariance of survivors to aggregate industry productivity growth. For Chile first and last year in the sample are 1995 and 2007, for Colombia 2000 and 2011, for Mexico 2003 and 2011, and for Peru 2007 and 2010

Table 4 presents unweighted means across 2-digit industries by country and for selected years. The sum of the components equals the change in aggregate productivity at the 2-digit level.¹⁸ Figure 3 reports the results of our dynamic decomposition of the overall manufacturing sector by year as a weighted average of 2-digit industry values. Consistently with our previous results, we find that the within-firm productivity component (the change in productivity of the incumbents or survivors) is more important than all other components for the aggregate manufacturing sector, although this is true for Colombia and Mexico more than for Chile and Peru. The average productivity of the survivors is generally positive and higher than the overall contribution of reallocation (the sum of the contribution of entrants, exiters and the change in covariance of the survivors), but not in years where weighted productivity growth is negative. In most cases, in years where aggregate productivity growth is positive, the contribution of reallocation is also generally positive albeit small.

¹⁸ In light of change in stratification methodology in 2011, the Peruvian sample is restricted to the 2007–2010 period to estimate the dynamic decompositions. Only the decomposition of the growth in productivity levels (rather than log-levels) is proposed. This is coherent with the strategy followed for the static decomposition, itself motivated by Van Biesebroeck (2008).

In years displaying negative aggregate productivity growth, the change in unweighted productivity of survivors is also negative, consistent with the fact that this component is on average more important, in the short-term at least, than the reallocation forces in determining aggregate productivity dynamics. In these periods, the total reallocation contributions are usually positive, albeit small, and mostly driven by the change in the covariance of survivors. This was the case for the Great Recession years as well, in the two out of three of the countries for which we have data (Colombia, Mexico). It suggests that crises have so far represented an opportunity to restructure production in the manufacturing sectors, and in particular a way to transfer resources towards more productive economic agents. The contribution of entrants to productivity growth, however, was *negative* in Colombia and Peru but not in Mexico. This behavior aligns Mexico and contrasts Colombia and Peru with the results of productivity dynamics in the U.S. during the Great Recession (Foster et al. 2016a), which is likely driven by cross-country differences in: the use of capital by entrants versus survivors; by learning; the extent to which pro-competitive forces impose a selection on entrants; or simply price differences between entrants and survivors that our industry-level deflation was not able to account for.

Exiters, instead, contributed positively, albeit little, to productivity growth in Chile, Colombia and Peru during crisis periods, thus suggesting that crises may have contributed to purge these economies from low-performing firms. These descriptive results, by pointing at the potentially “cleansing” role of recessions at least for Chile, Colombia and Peru, are in line with the evidence presented by Davis and Haltiwanger (1992) and Foster et al. (2016a) for the United States. They find that recessions have been “cleansing” in the U.S. manufacturing sector after World War II, but also that the Great Recession was different, as it was characterised by a smaller gap between the exit rates of low and high productivity firms, and therefore by a milder “cleansing” effect. The relatively short time series in the data at our disposal makes it impossible to provide similar inference in historical perspective, but we do find descriptive evidence that the Great Recession was different from other periods of negative labor productivity growth, insofar as the productivity of exiters was higher than that of survivors in Colombia and especially Mexico during that period, and therefore depressed aggregate productivity growth in the manufacturing sector.

Baily et al. (1992), Foster et al. (2001), Bartelsman et al. (2004, 2009), or Melitz and Polanec (2015), find a similar prominence in the contribution of productivity growth for the survivors to aggregate productivity growth, although all these studies differ in time frame and time-span over which the decomposition is calculated, choice of productivity measure, and country analyzed. Other recent studies, instead, find large reallocation effects, such as Decker et al. (2017), who exploit the same Melitz–Polanec dynamic productivity decomposition, and three papers decomposing productivity growth using an alternative methodology (Petrin and Levinsohn 2012; Nishida et al. 2013, 2014).

Petrin and Levinsohn (2012) in particular decompose TFP growth in Chile between 1980 and 1995 and find that reallocation accounts for approximately 50% of aggregate productivity growth. They also show that the reallocation term of previous productivity decompositions by Baily et al. (1992), Griliches and Regev (1995) and Foster et al. (2001) tend to underestimate the contribution of reallocation relative to their new decomposition methodology. Previous methodologies for the decomposition of TFP growth, much like in the one applied in the present study, calculate aggregate productivity growth as a weighted change in plant-level technical efficiency terms, rather than as the difference between growth in aggregate final demand and in expenditure on inputs. Applying the same definition of aggregate productivity growth and decomposition technique to Chilean and Colombian data, Nishida et al. (2014) show that the correlation between the Baily et al. (1992) and Petrin and Levinsohn (2012) reallocation

Fig. 3 Firm-level dynamic decomposition (weighted average of manufacturing industries). *Note* Based on cleaned sample. Labor productivity is measured as deflated value added (in US\$) per employee. The graphs aggregate results of the decompositions at the 2-digit industry level using the industry's employment in total manufacturing employment

contributions to aggregate labor productivity growth can have any sign, and the reallocation contribution is much larger with the Petrin and Levinsohn (2012) decomposition. This evidence suggests caution is warranted in drawing too strong conclusions from the decompositions presented above, at least as far as the relative contribution of overall reallocation versus within-firm productivity growth is concerned.

5 Econometric estimation

The evidence presented so far suggests that countries and industries differ in the dynamics of the allocative efficiency component in driving overall productivity growth. The remaining part of this paper investigates what can explain these differences. It focuses in particular on the role of public policies, regulations, and institutions. Selected characteristics of the labor, product, infrastructure, and financial markets may hinder the mobility of economic agents, and therefore affect allocative efficiency at the industry or country level.

When assessing the effects of policies on allocative efficiency we cannot ignore the possibility that public policies are likely to be endogenous, as common shocks can affect both

productivity dynamics and policy decisions simultaneously. Furthermore, causality may go from allocative efficiency to policies, for instance in case policy makers recognized the low productivity of a given industry compared to other countries and decided to raise regulatory barriers to protect firms and employment. We tackle these estimation issues by relying on a difference-in-difference approach that builds on the original paper by Rajan and Zingales (1998), where we estimate the policy impact by comparing industries which have different exposure (or dependence) to that specific policy. The identification assumption is that firms operating in industries which are more exposed to a certain policy (e.g. firms that are more labor intensive) should be disproportionately more affected by changes in that policy (e.g. labor market regulations). In more formal terms, we estimate:

$$\ln(y)_{cst} = \beta_0 + \beta_1 Policy_{ct} + \beta_2 Exposure_s + \beta_3 (Policy_{ct} * Exposure_s) + \alpha_t + \gamma_{cs} + e_{cst} \quad (3)$$

where “y” is our measure of an industry allocative efficiency (from either the static or dynamic decompositions), “Policy” is a country-time specific regulatory or policy measure, while “Exposure” is the industry-specific degree of exposure of the industry to the regulation, as measured in the United States in 1999 (or earlier, if 1999 is not available). The choice of a measure for the United States aims at further limiting the endogeneity concerns which may be affecting our estimations. The primary coefficient of interest is β_3 , where a positive interaction term signals that benefits from the policy measure are larger for sectors which are more exposed to the policy than for those which are less exposed to it.

Our specification is estimated including a large set of fixed effects, to limit the scope of omitted variable biases. These include country-industry fixed effects and thus control for all time-invariant macroeconomic and country-wide characteristics which could affect our estimation as well as industry-level characteristics. Importantly, the industry fixed effects control for time-invariant differences in technology and demand across sectors, and absorb β_2 . This specification is further strengthened by introducing country-time fixed effects, which are perfectly collinear with the policy measure and capture time-varying country-wide factors which are constant across sectors. As a consequence, the identification of β_3 only relies on variation between sectors within countries. Lastly, following Angrist and Pischke (2008) recommendations when working with aggregated micro-level data as it is the case here, Eq. (3) will be estimated reweighting each observation by the number of firms operating in the industry-country-year, whose variation is summarized by the dependent variable. These weights give more importance in the estimation results to the industries with a higher number of firms, which adds to the estimates’ ability to provide an accurate picture of the relationship between dependent and independent variables in the aggregate.

The empirical framework above helps minimize concerns about endogeneity biases in the estimated results. Nevertheless, it requires two assumptions for correct identification. First, the policy measure must affect the dependent variable directly and not through some determinant which was omitted from the empirical model. As mentioned, we tackle this point by introducing a number of fixed effects which should wash out any other country- or industry-specific time-invariant correlate to the dependent variable. As long as the remaining omitted variables play the same role for allocative efficiency in both high- and low-exposure industries, the coefficient of our main interest is estimated without bias.

Secondly, it must be possible to identify industries which are “naturally” more exposed to the given policy measure and where a marginal change in the policy restrictiveness affects the dependent variable (e.g. allocative efficiency) more strongly. Furthermore, this should not be itself determined by the dependent variable, to avoid reverse causality biases. As the identification strategy exploits the fact that the policy effect is stronger, the more exposed

the industry is to the policy measure, reverse causality would apply only if the policy measure was determined by the relative, e.g., allocative efficiency of a high-exposure sector compared to other manufacturing sectors. We assume that the industry's exposure in the United States is the "natural" one, which itself assumes that the United States represents the market with lowest regulatory distortions and highest allocative efficiency. The fact that our benchmark country is excluded from the dataset further reduces the potential concerns about endogeneity.¹⁹ Nevertheless, in the absence of a strong instrumental variable approach or of an experimental setting, our results should be interpreted cautiously.

6 Empirical hypothesis and results

Aggregate labor productivity in the overall economy corresponds to GDP per capita, which is commonly used to proxy the economic development of a country. As a consequence, changes in labor productivity represent an important policy objective for policy makers. The focus of the econometric analysis thus lies on the policy measures which can affect labor productivity growth in manufacturing through one of the two channels which can be identified with productivity decompositions, i.e. the allocation of resources across plants (the "between" or allocative efficiency term).²⁰ The specification including fixed effects described above is fit for the purpose, as discussed in the previous section. It remains important to identify which regulatory or policy measures we can appropriately measure for the four Latin American countries of interest, and which are most relevant for productivity dynamics. For this purpose, we rely on the existing literature and analyze selected aspects of contract enforcement, labor market regulations, product market regulations, and financial market regulations.

In particular, we analyze how changes in the cost of laying off employees can affect allocative efficiency differently across sectors which are more or less capital intensive.²¹ A long and established empirical literature supports the idea that stringent labor markets reduce employment turnover and may hamper productivity growth through limiting incentives for firms to hire or replace workers. More stringent labor regulations may imply lower entry rates or exit of firms (e.g. Haltiwanger et al. 2014), or job creation and destruction

¹⁹ The choice of using an excluded-country as benchmark has been criticized before. Ciccone and Papaioannou (2007, 2010) show that the further away the benchmark country (in our case, the U.S.) is from the true frictionless economy, the larger the bias towards zero in the policy coefficient. The estimates further suffer from an "amplification" bias, whereby the policy has a stronger (respectively, weaker) effect on the dependent variable for countries which have more similar (resp., different) industrial structure and regulations to the benchmark country ones. The sign of the resulting joint bias is a priori unknown. Ciccone and Papaioannou (2007, 2010) proposed instead to instrument the U.S. industry-level term with cross-country industry and policy information. As a result, the instrumented industry term varies with the "global" component of the U.S. industrial features only, and not with U.S. "idiosyncratic" features. As our sample is composed by few countries, the resulting instrument may be mis-specified and we decided not to follow on this path.

²⁰ In truth productivity differentials approximate and are the result of a number of differences among firms beyond technical efficiency, e.g. in costs and demand faced by the companies, but which we cannot identify in this analysis and with the data at hand (Foster et al. 2016a, b, c).

²¹ The sample is unbalanced due to the different data access we could obtain across country. In this econometric analysis, we restrict the sample to begin in 2000, in order for at least two countries to always be present. This results in 684 country-industry-year observations, which decrease to 501 in some specifications, due to missing values for the average number of years of schooling in the countries. The dependent variable is taken in hyperbolic log-sine transformation to allow for negative values. The resulting coefficients are therefore interpretable as semi-elasticities. Explanatory variables which are not dummies are standardized over the available years and country-sectors. Errors are both robust and clustered at the industry-country level.

among incumbent ones (Gómez-Salvador et al. 2004; Bravo-Biosca et al. 2016). What is more, by hindering firm growth and making it more costly to take risks, experiment, and innovate, stringent labor market regulations may hamper within-firm productivity growth too (Bassanini et al. 2009; Bartelsman et al. 2016; Bravo-Biosca et al. 2016).

A specific type of capital, i.e. the human one, also matters for aggregate productivity. While human capital can be included as an input in the production function and therefore plays a role in the definition of productivity, identifying a clear channel between human capital and economic growth has proved more challenging, because the two concepts are highly endogenous, and because human capital is often mis-measured (Sianesi and Van Reenen 2003; Prichett 2006; Delgado et al. 2014). We therefore introduce an interaction term between the average number of years of schooling for people of age 25–64 in the considered countries and the proportion of unskilled workers employed in the sector in the U.S. It seems that the role of skills for overall productivity growth is especially marked when education is coupled with absorptive capacity and the ability to adapt to technological change (Vandenbussche et al. 2006; Madsen 2014).

The literature describing the relationship between infrastructure (investment) and aggregate productivity is often inconclusive and characterized by estimation problems similar to those mentioned for human capital (de la Fuente 2010). Nevertheless, previous studies seem to support the hypothesis that infrastructure matters for productivity, especially in countries where the infrastructure network is at early stages of development. Better infrastructure decreases transaction costs, improves the use of production inputs, and exploits knowledge spillovers, which can compensate for the increased cost of congestion incurred by localities which are reached by new infrastructure (Straub 2008). To our knowledge, however, previous studies on the role of infrastructure for productivity growth do not focus on whether these gains materialize through firm-level efficiency improvements or better allocation of inputs across firms. The international trade literature, conversely, has examined these issues. While a synthesis of international trade research goes beyond the scope of the present paper, the implications of trade for aggregate productivity dynamics have been explored both theoretically (e.g. Melitz 2003; Eaton et al. 2011) and empirically (e.g. Alcalá and Ciccone 2004; Lileeva and Trefler 2010; Bloom et al. 2016). This research shows how aggregate productivity is shaped by imports or exports through the entry and exit of firms and the reallocation of inputs across heterogeneous firms.

A large literature has shown benefits of product market liberalization (either for the sector itself, or for upstream sectors) for firm-level and aggregate productivity growth (e.g. Nicoletti and Scarpetta 2003; Arnold et al. 2011b, 2015; Bourlès et al. 2013; Andrews and Cingano 2014). In more liberalized markets, unproductive firms are pressured to exit, as they cannot face the increased competition on the input and output markets, thus freeing resources and market shares for new potential entrants.²² The resulting competitive pressure also stimulates survivors to improve the quality of their output and to innovate, with

²² Competition on the product market stimulates innovation, too, although the relationship is often non-linear (Aghion et al. 2004, 2005, 2009). We therefore estimated how changes in regulatory measures correlate to productivity growth, depending on the degree of intensity of sectors in R&D spending (from the OECD ANBERD database), the only proxy of innovation at our disposal. Neither changes in the supply of education, nor in the structural reform index, nor in the financial development indicators of our choice (court interventionism and length of insolvency procedures) were found to significantly change productivity growth differently in R&D intensive vs non-R&D intensive sectors (results available on request). Many an explanation could motivate the lack of statistical correlation. For instance, few firms in each sector invest in R&D, R&D expenditure displays strong serial correlation, or the productivity-enhancing effect of R&D may take time to manifest itself.

positive consequences for firm-level productivity. A second stream of literature relates productivity to the degree of relationship-specificity or of complexity of products sold by the companies. Grossman and Helpman (2003) and Antras and Yeaple (2014) highlight that FDI and vertical integration are preferred to outsourcing when industries are more intensive in relationship-specific products and investments, while Antras and Helpman (2004) show that productivity is higher for vertically integrated firms than for outsourcing firms. Altomonte and Békés (2009) find that greater complexity of production is associated with higher productivity for both importers and especially exporters, while Yu et al. (2013) provide evidence that trade liberalization increases productivity in firms which produce more complex goods, and decreases that of firms with low complexity in production.

The last regulatory aspect of our interest in this study is financial development. Banerjee and Duflo (2005) proposed a model with fixed cost of production where credit market imperfections decrease entry and produce misallocation. Efficient firms are better equipped to overcome borrowing constraints (Midrigan and Xu 2014), but poor judiciary enforcement in a country with heterogeneous access to finance may hamper firms' growth and technology adoption (Amaral and Quintin 2010). As financial frictions can produce misallocation of capital and talent and depress productivity growth as a consequence, firms and industries characterized by higher dependence on external finance may see lower rates of productivity growth (Buera et al. 2011). More developed financial institutions increase the growth differential between high and low performing firms which are dependent on external finance, but while supporting a faster growth of top-performers, these institutions can also allow resources to flow into underperforming firms, which ties inputs to unproductive firms and lowers allocative efficiency (Bravo-Biosca et al. 2016).

We analyse the interaction between indicators of financial development and the ease of plants to access to credit,²³ as measured by the tangible capital intensity of plants in the sector, where tangible assets can be offered as collateral to obtain bank funding (Raddatz 2006). A second measure of external financial dependence is obtained from Rajan and Zingales (1998). Moreover, we test whether more complex productions require more sophisticated financial institution, in light of the fact that contracts are more difficult to write and enforce where transacted goods are more complex (i.e. require a larger number of inputs and therefore a larger number of transactions with suppliers, as in Nunn 2007). Lastly, the quality of financial institutions may affect differently plants in sectors displaying different managerial capabilities: on the one hand, competent managers may be able to navigate the economy even in more dire financial conditions, on the other hand more sophisticated management may be able to take advantage of the growth opportunities created by well developed financial institutions. Financial development is proxied here by the length of insolvency procedures and the degree of court involvement in the decisions by the bank supervisory authority (from the World Bank Doing Business survey and Barth et al. 2012), where for both measures the LAC countries of interest display lower values than the United States.

However, both measures of financial development have an ambiguous association with the allocative efficiency in the sector. The relative importance of courts may hamper or foster the growth of more productive firms, depending on whether courts are independent from political capture. Increasing the cost of bankruptcy can on the one hand worsen allocative efficiency, as even unproductive firms can survive and potentially reduce the range of opportunities for new entrants. This effect would be stronger for firms which are both

²³ The ease of plants to access to credit is negatively correlated to the plants external dependence from finance (see Raddatz 2006).

larger and more capital intensive, but also less efficient in exploiting economies of scale. On the other hand, higher costs of insolvency should discourage financial institutions from lending to less productive firms, improving resource allocation. At the same time, however, one would expect an increase in the cost of external finance, and especially for firms which rely on it to a greater extent and for young firms, which cannot rely on past profits to enter the market and stay in operation. If these firms are also especially productive, a higher cost of external finance would also imply a worsening of allocative efficiency in the economy.

6.1 Results: static decomposition

Our results for the static decomposition (Table 5, columns 1 and 5) suggest that an increase in the cost of laying off workers, while overall negative for allocative efficiency (results omitted but available on request), especially worsens allocation in capital-intensive sectors. A number of channels may be at play: higher capital intensity may proxy for the level of sophistication of production or the level of technological advancement of production, so that more binding regulation may hamper the plants' flexibility to adjust production according to the latest technological advancements which may be needed to remain competitive. This would be especially true if the countries under analysis are facing the challenge of a transition towards more ICT-intensive and labor-saving production. These sectors may also display the highest level of formality in employment, which would make regulatory change more binding and costly.

Columns 2 and 6 show instead that an increase in the skill supply in the economy *worsens* allocative efficiency in low-skill sectors relative to high-skill sectors. Growth in size of low-skill firms may be lower in an economy with higher supply of skills, where low-skill intensive workers have become relatively more expensive to hire. McGowan and Andrews (2015) further report that skill mismatch in the workplace is more frequent for young and educated workers in OECD countries, and that this has an adverse impact on firm productivity. If the LAC countries in this analysis suffer from similar mismatches, increasing the supply of skilled workers can worsen allocative efficiency by supplying skills to production which is less than capable to valorize them. These associations would be more relevant, the lower the mobility of workers across firms, suggesting that jointly determining the role of stringency of labor market conditions and the supply of skilled workers for productivity growth may incur collinearity issues.

Columns 3 and 7 of Table 5 show that increasing port efficiency would improve allocative efficiency in sectors which are more reliant on trade by sea. This is important, as all LAC countries in the sample have sea access and exploit it as a major instrument to interact with the international market. In this sense, this specification stands for other possible policy measures to evaluate the links between productivity and both infrastructure and connectivity to the international market. Therefore, the result on infrastructure can reflect the productivity-enhancing role of exposure to international trade.

In Table 5 columns 4 and 8, we estimate the relationship between industry productivity and a change in the structural reform index and the degree to which goods in the industry require relationship-specific inputs and investments, as we define "product complexity" here.²⁴ After

²⁴ The index of structural reforms is taken from Lora (2012) and summarizes several policy measures related to competition in the product and input markets. The indicator for product complexity is taken from Nunn (2007) and refers to the percentage of inputs in the industry which are neither traded in organized exchanges nor reference priced. The sectors displaying the highest complexity are: motor vehicles and other transportation equipment, electrical machinery, computers, electronic and optical equipment, and machinery not elsewhere classified; the sectors displaying the lowest complexity are: coke and oil extraction, tobacco, food and beverages, rubber and plastics, and pulp and paper.

Table 5 Regression on static decomposition (1)

	1	2	3	4	5	6	7	8
(Cost of firing) $\times$ (Capital/labor)	-0.567** (0.263)				-0.567* (0.290)			
(Years of schooling) $\times$ (% unskilled)		-0.813*** (0.203)				-0.813** (0.317)		
(Port efficiency) $\times$ (% Trade by sea)			0.369** (0.160)				0.369** (0.171)	
(Structural reform index) $\times$ (Product complexity)				-0.743** (0.375)				-0.743 (0.511)
N	684	501	684	684	684	501	684	684
SE	Robust	Robust	Robust	Robust	Clustered	Clustered	Clustered	Clustered

Based on the cleaned sample and restricted to years after 1999. The dependent variable is the logarithm of the term derived from the decomposition of labor productivity at the 2-digit industry level and in particular the OP gap, or covariance. All explanatory variables are standardised over the sample. The first term of each cross product refers to a country-level, time-varying indicator, the second term to an industry-invariant measure of intensity for the United States in 1999 or earlier; in case 1999 was missing. All regressions include country $\times$ year and industry $\times$ country fixed effects. Robust or clustered standard errors at the country-industry level in parentheses. ***significant at 1%; **significant at 5%; *significant at 10%.

a pro-competitive reform, sectors with less sophisticated products display a larger positive change in allocative efficiency than sectors with more sophisticated products. Sectors with less complex production could thus be benefiting the most from the liberalization and see the highest increase in entry of productive players. If pro-competitive reforms also increase the average size of survivors and reduce size heterogeneity by forcing the exit of the least productive and smallest plants, this is likely to happen more strongly for more complex production processes. The covariance term in these sectors would therefore decrease relative to that of sectors displaying less-sophisticated production. Lastly, it is possible that the institutions in the considered countries are not yet able to fully sustain the production of complex goods in a liberalized market. These “good but not good enough” reforms would reflect in poorer performance and downsizing of producers in high-complexity sectors more than in low-complexity sectors.

Our results on the role of financial development (Table 6, columns 3–4 and 7–8) highlight that extending the length of insolvency procedures worsens resource allocation in sectors which rely more heavily on external finance (or are less tangible capital intensive), thus suggesting that reallocation may be hampered by lower entry of new plants, and by excessive pressure on productive plants which rely on external finance. As these plants are especially dependent on an efficient financial system and can provide little collateral, they suffer from a deterioration of the financial development conditions in the country. The same conclusions can be reached from the estimations where the institutional variable is court supervision of the supervisory authority. The remaining columns of Table 6 instead suggest that insolvency and court activism worsen allocation in sectors which are better managed or produce more complex output than in sectors where these conditions do not apply. More complex production requires more advanced institutional settings to protect proprietary technologies and insure the enforcement of transactions which are hard to formalise in a contract. More complex production also requires better organisational capabilities, which may drive the sign of the coefficients on both interactions, although with lower magnitude and statistical significance in the case of organisational capabilities.

6.2 Results: dynamic decomposition

The decomposition presented in the previous section does not distinguish between continuing and new or exiting plants. However, regulatory distortions can prevent entry of potentially productive actors, or ensure the survival of unproductive ones, and affect survivors in a different manner. We therefore complement the analysis carried out on the basis of the Olley–Pakes decomposition with one exploiting the Melitz–Polanec decomposition of productivity growth. While the aggregate productivity underlying both static and dynamic decompositions is the same, the reallocation term (respectively, the change in average productivity of survivors) in the dynamic decomposition does not correspond to the change in covariance (resp. average productivity) calculated in the static decomposition. Indeed by construction the definitions are different, as entrant and exiter activity affects both terms in the Olley–Pakes decomposition, while entry and exit activity is reflected only in their own separate terms in the dynamic decomposition. Nevertheless, controlled correlations between the change in the static covariance (resp., average plant productivity) and the contribution of overall reallocation (resp. the change in average productivity of the survivors) to productivity growth yield a positive and strongly statistically significant correlation.

In light of the mentioned data constraints related to the identification of entrants and exiters, and the well known sensitivity contribution of net entry to productivity growth to measurement errors (Foster et al. 2001), we limit the analysis of allocative efficiency in

Table 6 Regression on static decomposition (2)

	1	2	3	4	5	6	7	8
Panel A								
(Court involvement)×(Tangibility)	0.215** (0.107)				0.215*** (0.036)			
(Court involvement)×(External finance dependence)		-0.219** (0.099)				-0.219 (0.149)		
(Years insolvency resolution)×(Tangibility)			0.321* (0.184)				0.321*** (0.109)	
(Years insolvency resolution)×(External finance dependence)				-0.408** (0.181)				-0.408** (0.178)
N	684	684	684	684	684	684	684	684
SE	Robust	Robust	Robust	Robust	Clustered	Clustered	Clustered	Clustered
Panel B								
(Court involvement)×(Organisational investment)	-0.100** (0.046)				-0.100 (0.079)			
(Court involvement)×(Product complexity)		-0.268*** (0.095)				-0.268* (0.131)		
(Years insolvency resolution)×(Organisational investment)			-0.179 (0.109)				-0.179 (0.109)	
(Years insolvency resolution)×(Product complexity)				-0.322** (0.152)				-0.322** (0.123)
N	684	684	684	684	684	684	684	684
SE	Robust	Robust	Robust	Robust	Clustered	Clustered	Clustered	Clustered

Based on the cleaned sample and restricted to years after 1999. The dependent variable is the logarithm of the term derived from the decomposition of labor productivity at the 2-digit industry level, i.e. the OP gap, or covariance. All explanatory variables are standardised over the sample. The first term of each cross product refers to a country-level, time-varying indicator, the second term to an industry-invariant measure of intensity for the United States in 1999 or earlier, in case 1999 was missing. *Panel A* and *Panel B* differ by the choice of explanatory variables at the industry level. All regressions include country×year and industry×country fixed effects. Robust or clustered standard errors at the country-industry level in parentheses. ***significant at 1%; **significant at 5%; *significant at 10%

Table 7 Regression on dynamic decomposition (1)

	1	2	3	4	5	6	7	8
(Cost of firing) $\times$ (Capital/labor)	-0.020* (0.011)				-0.020* (0.011)			
(Years of schooling) $\times$ (% unskilled)		-0.024 (0.021)				-0.024 (0.017)		
(Port efficiency) $\times$ (% trade by sea)			0.011 (0.006)				0.011* (0.006)	
(Structural reform index) $\times$ (Product complexity)				-0.021 (0.022)				-0.021 (0.020)
N	588	406	588	588	588	406	588	588
SE	Robust	Robust	Robust	Robust	Clustered	Clustered	Clustered	Clustered

Based on the cleaned sample and restricted to years after 1999. The dependent variable is the contribution of reallocation to aggregate productivity growth as derived from the Melitz–Polanec decomposition of labor productivity at the 2-digit industry level: the sum of contributions of entrants, exiters and the change in the OP gap for survivors. All explanatory variables are standardised over the sample. The first term of each cross product refers to a country-level, time-varying indicator, the second term to an industry-invariant measure of intensity for the United States in 1999 or earlier, in case 1999 was missing. Estimations are carried out in first differences. All regressions further include country $\times$ year and industry fixed effects. Robust and clustered standard errors at the country-industry level in parentheses. ***significant at 1%; **significant at 5%; *significant at 10%

Table 8 Regression on dynamic decomposition (2)

	1	2	3	4	5	6	7	8
Panel A								
(Court involvement) $\times$ (Tangibility)	0.024 (0.026)				0.024* (0.012)			
(Court involvement) $\times$ (External finance dependence)		-0.052*** (0.020)				-0.052*** (0.019)		
(Years insolvency resolution) $\times$ (Tangibility)			0.041** (0.017)				0.041** (0.016)	
(Years insolvency resolution) $\times$ (External finance dependence)				-0.027** (0.012)				-0.027** (0.012)
N	588	588	588	588	588	588	588	588
SE	Robust	Robust	Robust	Robust	Clustered	Clustered	Clustered	Clustered
Panel B								
(Court involvement) $\times$ (Organisational investment)	-0.018 (0.012)				-0.018** (0.008)			
(Court involvement) $\times$ (Product complexity)		-0.043** (0.019)				-0.043*** (0.016)		
(Years insolvency resolution) $\times$ (Organisational investment)			-0.007 (0.010)				-0.007 (0.010)	
(Years insolvency resolution) $\times$ (Product complexity)				-0.022*** (0.003)				-0.022*** (0.003)
N	588	588	588	588	588	588	588	588
SE	Robust	Robust	Robust	Robust	Clustered	Clustered	Clustered	Clustered

Based on the cleaned sample and restricted to years after 1999. The dependent variable is the contribution of reallocation to aggregate productivity growth as derived from the Melitz–Polanece decomposition of labor productivity at the 2-digit industry level; the sum of contributions of entrants, exiters and the change in the OP gap for survivors. All explanatory variables are standardised over the sample. The first term of each cross product refers to a country-level, time-varying indicator, the second term to an industry-invariant measure of intensity for the United States in 1999 or earlier, in case 1999 was missing. *Panel A* and *Panel B* differ by the choice of explanatory variables at the industry level. Estimations are carried out in first differences. All regressions further include country $\times$ year and industry fixed effects. Robust or clustered standard errors at the country $\times$ industry level in parentheses. *** significant at 1%; ** significant at 5%; * significant at 10%

this section to the contribution of the overall reallocation term to aggregate productivity growth, i.e. of the sum of contributions of entrants, exiters, and the covariance of size and productivity for the continuers. As the contributions are expressed in changes, the regression equation resembles (3) above, but is estimated in first differences, and the dependent variable is not taken in logarithms. All of the above motivates the differences in estimates when based on static vs dynamic decompositions.

Tables 7 and 8 report the regression results for the same policy determinants as in Tables 5 and 6 respectively. The correlations between policy measures and the contributions of reallocation to productivity growth have the same sign as the correlations with changes in the static covariance term, although statistical significance is lost for selected policy dimensions of Table 7. The association between changes in financial development and allocative efficiency remains strong and consistent with the descriptions in the previous paragraph: the length of insolvency procedures and greater discretionary power of courts worsen the allocation of resources in sectors which rely more heavily on external finance, and may force surviving plants to improve their efficiency (statistical significance is low here, especially for court involvement). As more complex production requires more advanced institutional settings and greater investor rights, a higher cost of insolvency and court interventionism are found to worsen allocation in sectors which are better managed or produce more complex output. The associations of these proxies of financial development with changes in the productivity of continuers are instead found to be insignificantly different between sectors with high and low exposure to the institutional characteristics.

7 Conclusions

Understanding the drivers of productivity growth is a first-order question in Latin America, as productivity growth in the region has been sluggish historically, and lagged significantly behind that of its northern neighbor, the United States (IDB 2010; IMF 2014). For the first time we have performed a comparative analysis of productivity decompositions at the plant level for various Latin American countries, with a focus on the decade of the 2000s. The main purpose of the analysis is the description of the contribution of allocative efficiency to manufacturing productivity (growth) in these regions, and the uncovering of which framework conditions could be leveraged to improve such contributions and aggregate productivity as a consequence.

First, we evaluated the extent to which aggregate productivity growth (in the manufacturing sector) is driven by growth in productivity at the firm level or by reallocation of employment shares across establishments. While sectoral and country heterogeneity are important and reduce the scope for strong conclusions from a descriptive analysis, we show that plant-level productivity (growth) has contributed the most to aggregate productivity (growth), with reallocation between plants within sectors accounting for at most 37% of overall productivity in a given 2-digit sector. The reallocation contribution to industry-level productivity growth in manufacturing is usually positive during economic downturns, highlighting a positive (albeit small) role for economic crises to improve manufacturing productivity. The average cross-industry contributions of entry and exit to manufacturing productivity growth are usually small and not univocal in sign across country.

Second, building on the previous result, we investigated the policy determinants of the contribution of allocative efficiency to aggregate productivity growth. At the aid of difference-in-difference fixed-effect regressions following Rajan and Zingales (1998), we estimate the policy impact by comparing industries which have different exposure (or dependence) to that specific policy. We evaluate the interaction of a number of country-level framework conditions and industry-level “exposure” variables, and find that product market, education and financial market reforms play an especially relevant role in the dynamics of allocative efficiency. This is done for the first time, to our knowledge, on the basis of the results of both static and dynamic productivity decompositions. The latter allows investigating the importance of policies in shaping not productivity levels, but productivity growth.

Our results point toward an agenda to understand allocative efficiency and aggregate productivity growth as a consequence, and can contribute to the recent debate on the productivity slowdown in OECD countries. Future analysis could investigate how policies shape total factor productivity differently from labor productivity growth, and take better account for role of prices and demand in determining productivity dynamics—albeit this is unfeasible with the data used in the current analysis. Improvements in the quality of data could also pave the road to a separate investigation of the contribution of entrants and exiters to aggregate productivity growth, which the present paper broadly abstracted from, in light of changes over time in the sampling strategy underlying the datasets used. The robustness of results could also be tested using a different decomposition technique, such as the one proposed by Petrin and Levinsohn (2012). Lastly, policies different from those used here may have an impact on productivity dynamics. While such an extension could provide interesting insights, it should take into account whether data are available and display sufficient time and country variation to allow for robust econometric estimation.

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Appendix 1: Micro data construction

We have access to establishment-level panel data sets for Chile (Encuesta Nacional Industrial Anual—ENIA), Colombia (Encuesta Anual Manufacturera, EAM), Mexico (Encuesta Industrial Anual, EIA), as well as a firm-level panel of firms in Peru (Encuesta Económica Anual, EEA). This was possible thanks to the respective national institutes of statistics (DANE, INE, INEI, INEGI). These data sets contain accounting information on plants in the manufacturing sector for 1995–2007 for Chile, 2000–11 for Colombia, 2003–11 for Mexico, 2007–2012 for Peru. In this annex, we supplement the information on eligibility and coverage of the manufacturing surveys that was provided in the main text.

Data cleaning

As our analysis requires non-missing observations for value added and employment in particular, we dropped all observations without information for value added per employee and industry classification, as well as those reporting negative employment and value added. In a further effort to limit the extent of misreporting, we also dropped observations with positive value added but zero employment; as a consequence, we excluded the possibility of sole proprietorship, which we deemed more unlikely in manufacturing. We treated the presence of extreme values in the resulting sample by truncating the distribution of value added and growth in value added at 1 and 99%.

As value added was not directly reported in the data set, we constructed it as the sum between (deflated) revenues from sales, minus the (deflated) cost of raw (either domestic or imported) materials and the (deflated) cost of electricity. If any component of this sum is missing, the result is also missing.

The resulting sample has missing values for the Chilean Tobacco sector, the Colombian Office Equipment production sector, the Mexican Transportation Equipment sector, and the Tobacco, Oil, and Office, Communication and Medical Equipment producing sectors.

Industry classification and conversion

Each of the micro-level surveys used in this study follows a different industry classification. The Chilean ENIA, Colombian EAM and Peruvian EEA classify manufacturing plants according to a four-digit International Standard Industrial Classification (ISIC3 or ISIC4) classification specifically adapted to the Chilean and Colombian context, containing respectively 113, 142 and 125 sectors. The Mexican EIA uses a six-digit classification inspired by the North American Industry Classification System (NAICS) for 2002 and 2007 (*Système de classification des industries de l'Amérique du Nord (SCIAN) 2002 and 2007*), displaying 231 industries.

The use of different industry classifications would have hindered the cross-country comparison of descriptive statistics and productivity decompositions. We created a new industry classification for manufacturing, which could include all national classifications, on the basis of existing NAICS 2002-NAICS 2007, NAICS-SCIAN, ISIC3 (Colombia)-ISIC 3.1 (international), ISIC3.1-ISIC4 (international) and NAICS 2002-ISIC3.1 (international) conversion tables. The resulting classification we use contains 104 4-digit classes and is broadly inspired by the international ISIC 3.1 breakdown.

One ISIC 3.1 four-digit class and seven six-digit NAICS 2002 classes have no correspondence in the new classification.

In constructing this new industrial classification, we first converted the national classifications into either NAICS 2002 or ISIC 3.1. A one-to-many correspondence between a four-digit ISIC 3.1 and a six-digit NAICS 2002 code also resulted in the use of the ISIC 3.1 code (this happened for 281 of 473 U.S. NAICS manufacturing classes). In taking into consideration the numerous many-to-many correspondences between NAICS 2002 and ISIC 3.1, we followed these principles:

1. When one of the multiple ISIC 3.1 codes corresponding to a single NAICS 2002 code was not classified as manufacturing in the ISIC 3.1 classification, we dropped this ISIC 3.1 code altogether. This happened for eight six-digit NAICS codes.

2. When the NAICS 2002 classification was specific enough, we searched for the corresponding products in the ISIC 3.1. A description table for the ISIC 3.1 code can be found at <http://unstats.un.org/unsd/statcom/doc02/isic.pdf>.
3. When in doubt about the attribution of a certain six-digit NAICS code to an ISIC code, we also took into consideration the meaning of the five- and four-digit NAICS codes.
4. When the “predominant meaning” of an NAICS code was clear once aggregating two or more of the proposed four-digit ISIC codes in the NAICS-ISIC conversion table, we merged the different ISIC codes. We limited the number of cases in which this happened, as it reduced the number of final available industry codes. In most cases, the merged ISIC codes refer to the same two- or three-digit ISIC classes.
5. We dropped seven NAICS six-digit codes, whose meaning could not be linked to any single ISIC or combination of ISIC codes.

Deflation

All financial information in the different manufacturing surveys is reported in nominal terms. We therefore deflate these values with an appropriate deflator in base 2005. We then convert them to thousands of U.S. dollars using the appropriate (yearly) exchange rate from the World Bank.

To deflate *sales* we use six-digit producer index prices for Mexico, 4 digit ones for Chile, and a manufacturing-level producer price index for Colombia and Peru.²⁵ For *material inputs*, we use the appropriate four-digit producer price index for Chile and for Mexico (the latter based on the CMAE—classification—Catálogo Mexicano de Actividades Económicas), and a manufacturing-wide deflator for Colombia and Peru. Expenditure for electricity, was deflated using the producer price index for the electricity sector in all countries but Peru, where this expenditure is not available. Finally, we used the consumer price index to deflate labor costs.

For Colombia and Mexico capital investment is deflated using three-digit price indexes for investment from the U.S. Bureau of Labor Statistics (BLS), which we adjust by the exchange rate between US\$ and the country currency. The BLS provides prices deflators for different types of investment: all capital goods, equipment, structures, land, intellectual property products, and inventories. We exploit the first three prices for, respectively, all investments, investment in machinery, and investment in buildings. Where available *information and communications technology (ICT) capital investment* was deflated using the price of gross output for the “information-communications-technology-producing industries” elaborated by the Bureau of Economic Analysis²⁶ and adjusted by the exchange rate. We deflated *investment in transportation equipment* by the country-specific producer price index for the transportation sector.

²⁵ For Colombia a more disaggregated producer price index time series was available from 2006 onwards only, at the time of writing.

²⁶ This is a synthetic sector covering hardware- and software-producing industries, including computer and electronics production, software publishing, telecommunications, data processing, Internet publishing, web portals, computer system designs, and related services.

Variable construction

The ideal measure of the capital stock embodied in the plants' production would be the replacement value of capital. Unfortunately, this is not available in the micro-data surveys we have access to. We create instead a measure of the plants' capital stock at book value, i.e. the depreciated value at which capital assets were purchased. We assume that the book value in the first year of the sample corresponds to the capital replacement value. We then construct the value of capital for the following years using the perpetual inventory method (PIM) according to the following equality:

$$K_{ijt} = K_{ijt-1}(1 - \delta_{jt-1}) + I_{ijt-1}$$

For $t \in [1995, 2007]$ for Chile, $t \in [2001, 2011]$ for Colombia, $t \in [2004, 2011]$ for Mexico. I_{ijt-1} denotes investment, or the purchase of new capital goods (which is reported in the data sets), and K_{ijt} is the result of the calculation of capital stocks in the year. δ_{jt} is the depreciation rate of capital. All surveys considered contain information on depreciation rates by type of capital. To limit the impact of possible misreporting, in the PIM we use the median of the two-digit sector depreciation rate from the data, where values above 100% and below 0% of capital stock were winsorized. Once we obtained a time series for the capital stock of each type of capital (buildings, equipment, ICT, and transportation, if available), we aggregated them into two variables, one for total capital and another for total capital except buildings and structures.

Appendix 2: Industry- and country-level framework data

The table below summarises the information exploited by this analysis in terms of policy levers potentially affecting allocative efficiency and average firm productivity in the economy, as well as the degree of exposure of manufacturing industries to those policies.

Variable	Definition	Source
Country level		
Court involvement	The degree to which the banking supervisory authority is independent from court rulings. The higher this index is, the less independent the supervisory authority is	Barth et al. (2012)
Accounting practices	The type of accounting practices used (the higher the better)	Barth et al. (2012)
Resolving insolvency	Years needed to resolve insolvency	World Bank Doing Business
Years of schooling	Years of schooling for population older than 25 year-old	UNESCO
Cost of firing	Expected cost of firing (number of months)	Lora (2012)
Structural reform index	Structural reform index. The higher, the more liberalised the country is	Lora (2012)
Port efficiency	Technical efficiency of container ports	Sarriera et al. (2013)
Industry level (USA)		

Variable	Definition	Source
Tangibility	Sum of fixed assets and depreciation, divided by operating revenues. Median value among firms in the industry, 2000	ORBIS©
Financial dependence	Capital expenditure not funded by internal funds divided by total capital expenditure	Rajan and Zingales (1998)
Low-skill intensity	Share of industry's workforce with low-skilled occupation (ILO-based)	U.S. CPS
Capital intensity	Total capital assets in the industry over employment	OECD STAN
Product complexity	Proportion of industry's value added which is priced neither through organized markets nor with reference prices (conservative approach). Values were converted from ISIC2 to ISIC3 using value added shares and the appropriate conversion table	Nunn (2007)
Organisational capabilities	Industry's investment in organizational capital divided by output. Investment is the sum over the wage bill of the industry's employees who are performing organizational-intensive tasks on the job place	Le Mouel et al. (2016), OECD STAN
Share of trade by sea	Share of trade value added in the industry transported by sea	Cristea et al. (2013)

References

- Aghion, P., Bloom, N., Blundell, R., Griffith, R., & Howitt, P. (2005). Competition and innovation: An inverted-U relationship. *Quarterly Journal of Economics*, 120(2), 701–728.
- Aghion, P., Blundell, R., Griffith, R., Howitt, P., & Prantl, S. (2004). Entry and productivity growth: Evidence from microlevel panel data. *Journal of the European Economic Association*, 2(3), 265–276.
- Aghion, P., Blundell, R., Griffith, R., Howitt, P., & Prantl, S. (2009). The effects of entry on incumbent innovation and productivity. *The Review of Economics and Statistics*, 91(1), 20–32.
- Alcalá, F., & Ciccone, A. (2004). Trade and productivity. *The Quarterly Journal of Economics*, 119(2), 613–646.
- Altomonte, C., & Békés, G. (2009). *Trade complexity and productivity*. KITeS working papers 016.
- Amaral, P., & Quintin, E. (2010). Limited enforcement, financial intermediation, and economic development: A quantitative assessment. *International Economic Review*, 51(3), 785–811.
- Andrews, D., & Cingano, F. (2014). Public policy and resource allocation: Evidence from firms in OECD countries. *Economic Policy*, 29(78), 253–296.
- Angrist, J. D., & Pischke, S. (2008). *Mostly harmless econometrics: An empiricist's companion*. Princeton: Princeton University Press.
- Antras, P., & Helpman, E. (2004). Global sourcing. *Journal of Political Economy*, 112(3), 552–580.
- Antras, P., & Yeaple, S. R. (2014). *Multinational firms and the structure of international trade. Handbook of international economics*. Elsevier.
- Arnold, J. M., Javorcik, B., & Mattoo, A. (2011a). Does service liberalization benefit manufacturing firms? Evidence from the Czech Republic. *Journal of International Economics*, 85(1), 136–146.
- Arnold, J. M., Javorcik, B., & Mattoo, A. (2015). Services reform and manufacturing performance: Evidence from India. *The Economic Journal*, 126(590), 1–39.

- Arnold, J. M., Nicoletti, G., & Scarpetta, S. (2011b). Regulation, resource reallocation and productivity growth. *EIB Papers*, 16(1), 90–115.
- Baily, M. N., Hulten, C., Campbell, D., Bresnahan, T., & Caves, R. E. (1992). Productivity dynamics in manufacturing plants. *Brookings papers on economic activity: Microeconomics*, pp. 187–267.
- Banerjee, A. V., & Duflo, E. (2005). Growth theory through the lens of development economics. In P. Aghion & S. N. Durlauf (Eds.), *Handbook of economic growth* (Vol. 1, pp. 473–552). Elsevier.
- Bartelsman, E., Gautier, P. A., & Wind, J. (2016). Employment protection, technology choice, and worker allocation. *International Economic Review*, 57, 787–826.
- Bartelsman, E., Haltiwanger, J., & Scarpetta, S. (2004). *Microeconomic evidence of creative destruction in industrial and developing countries*. IZA Discussion Papers 1374, Institute for the Study of Labor (IZA), Bonn, Germany.
- Bartelsman, E., Haltiwanger, J., & Scarpetta, S. (2009). Measuring and analyzing cross-country differences in firm dynamics. In T. Dunne, J. Bradford Jensen, & M. J. Roberts (Eds.), *Producer dynamics: New evidence from micro data* (pp. 15–76). Chicago: University of Chicago Press.
- Bartelsman, E., Haltiwanger, J., & Scarpetta, S. (2013). Cross-country differences in productivity: The role of allocation and selection. *American Economic Review*, 103(1), 305–334.
- Barth, J. R., Caprio, G., & Levine, R. (2012). *The evolution and impact of bank regulations*. Policy Research Working Paper No. 6288. World Bank.
- Bassanini, A., Nunziata, L., & Venn, D. (2009). Job protection legislation and productivity growth in OECD countries. *Economic Policy*, 24(58), 349–402.
- Bloom, N., Draca, M., & van Reenen, J. (2016). Trade induced technical change? The impact of Chinese imports on innovation, IT and productivity. *Review of Economic Studies*, 83(1), 87–117.
- Bourlès, R., Cetté, G., Lopez, J., Mairesse, J., & Nicoletti, G. (2013). Do product market regulations in upstream sectors curb productivity growth? Panel data evidence For OECD countries. *The Review of Economics and Statistics*, 95(5), 1750–1768.
- Bravo-Biosca, A., Criscuolo, C., & Menon, C. (2016). What drives the dynamics of business growth? *Economic Policy*, 31(88), 703–742.
- Buera, F. J., Kaboski, J. P., & Shin, Y. (2011). Finance and development: A tale of two sectors. *American Economic Review*, 101(5), 1964–2002.
- Byrne, D., Fernald, J., & Reinsdorf, M. (2016). *Does the United States have a productivity slowdown or a measurement problem?* Brookings Papers on Economic Activity.
- Ciccone, A., & Papaioannou, E. (2007). Red tape and delayed entry. *Journal of the European Economic Association*, 5(2–3), 444–458.
- Ciccone, A., & Papaioannou, E. (2010). *Estimating cross-industry cross-country models using benchmark industry characteristics*. Economics Working Papers No 504, Department of Economics and Business, Universitat Pompeu Fabra.
- Cristea, A., Hummels, D., Puzzello, L., & Avetisyan, M. (2013). Trade and the greenhouse gas emissions from international freight transport. *Journal of Environmental Economics and Management*, 65(1), 153–173.
- Davis, S. J., & Haltiwanger, J. (1992). Gross job creation, gross job destruction, and employment reallocation. *The Quarterly Journal of Economics*, 107(3), 819–863.
- de la Fuente, A. (2010). *Infrastructures and productivity: An updated survey*. UFAE and IAE Working Papers 831.
- Decker, R., Haltiwanger, J., Jarmin, R. S., & Miranda, J. (2017). Declining dynamism, allocative efficiency, and the productivity slowdown. *American Economic Review*, 107(5), 322–326.
- Delgado, M., Henderson, D. J., & Parmeter, C. F. (2014). Does education matter for economic growth? *Oxford Bulletin of Economics and Statistics*, 76(3), 334–359.
- Eaton, J., Kortum, S., & Kramarz, F. (2011). An anatomy of international trade: Evidence from French firms. *Econometrica*, 79(5), 1453–1498.
- Fernald, J. (2015). Productivity and potential output before, during and after the great recession. *NBER Macroeconomics Annual*, 29(1), 1–51.
- Foster, L., Grim, C., & Haltiwanger, J. (2016a). Reallocation in the great recession: Cleansing or not? *Journal of Labor Economics*, 34(S1), S293–S331.
- Foster, L., Grim, C., Haltiwanger, J., & Wolf, Z. (2016b). Firm-level dispersion in productivity: Is the devil in the details? *American Economic Review*, *American Economic Association*, 106(5), 95–98.
- Foster, L., Haltiwanger, J., & Krizan, C. J. (2001). Aggregate productivity growth. Lessons from microeconomic evidence. In C. R. Hulten, E. R. Dean, & M. J. Harper (Eds.), *New developments in productivity analysis* (pp. 303–372). Chicago: University of Chicago Press.
- Foster, L., Haltiwanger, J., & Syverson, C. (2008). Reallocation, firm turnover, and efficiency: Selection on productivity or profitability? *American Economic Review*, 98(1), 394–425.

- Foster, L., Haltiwanger, J., & Syverson, C. (2016c). The slow growth of new plants: Learning about demand? *Economica*, 83(329), 91–129.
- Gómez-Salvador, R., Messina, J., & Vallanti, G. (2004). Gross job flows and institutions in Europe. *labor Economics*, 11(4), 469–485.
- Grossman, G. M., & Helpman, E. (2003). Outsourcing versus FDI in industry equilibrium. *Journal of the European Economic Association*, 1(2–3), 317–327.
- Griliches, Z., & Haim, R. (1995). Firm productivity in Israeli industry 1979–1988. *Journal of Econometrics*, 65(1), 175–203.
- Haltiwanger, J., Kulick, R. B., & Syverson, C. (2018). *Misallocation measures: The distortion that ate the residual*. NBER Working Paper N. 24199.
- Haltiwanger, J., Scarpetta, S., & Schweiger, H. (2014). Cross country differences in job reallocation: The role of industry, firm size and regulations. *labor Economics*, 26(C), 11–25.
- Harrison, A. E., Martin, L. A., & Nataraj, S. (2013). Learning versus stealing: How important are market-share reallocations to India's productivity growth? *World Bank Economic Review*, 27(2), 202–228.
- Hsieh, C. T., & Klenow, P. J. (2009). Misallocation and manufacturing TFP in China and India. *Quarterly Journal of Economics*, 124(4), 1403–1448.
- Inter-American Development Bank. (2010). *The age of productivity*. Washington, DC: Palgrave MacMillan.
- International Monetary Fund. (2014). Regional economic outlook update: Western hemisphere—Latin America and the Caribbean. Technical Report.
- Le Mouel, M., Marcolin, L., & Squicciarini, M. (2016). *Investment in organisational capital: Methodology and panel estimates*. SPINTAN Working Paper, p. 21.
- Levinsohn, J., & Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. *The Review of Economic Studies*, 70(2), 317–341.
- Lileeva, A., & Trefler, D. (2010). Improved access to foreign markets raises plant-level productivity for some plants. *Quarterly Journal of Economics*, 125(3), 1051–1099.
- Lora, E. (2012). *Structural reforms in Latin America: What has been reformed and how to measure it (updated version)*. Inter-American Development Bank Working Paper Series, p. 346.
- Madsen, J. B. (2014). Human capital and the world technology frontier. *The Review of Economics and Statistics*, 96(3), 676–692.
- McGowan, M. A., & Andrews, D. (2015). *Skill mismatch and public policy in OECD Countries*. OECD Economics Department Working Papers 1210, OECD Publishing.
- Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *Econometrica*, *Econometric Society*, 71(6), 1695–1725.
- Melitz, M. J., & Polanec, S. (2015). Dynamic Olley–Pakes productivity decomposition with entry and exit. *The Rand Journal of Economics*, 46(2), 362–375.
- Midrigan, V., & Xu, D. Y. (2014). Finance and misallocation: Evidence from plant-level data. *American Economic Review*, 104(2), 422–458.
- Nicoletti, G., & Scarpetta, S. (2003). Regulation, productivity and growth: OECD evidence. *Economic Policy*, 18(36), 9–72.
- Nishida, M., Petrin, A., & Polanec, S. (2014). Exploring reallocation's apparent weak contribution to growth. *Journal of Productivity Analysis*, 42, 187–210.
- Nishida, M., Petrin, A., Rotemberg, M., & White, T. K. (2013). Are we undercounting reallocation's contribution to growth? Working Papers 13-55r, Center for Economic Studies, U.S. Census Bureau.
- Nunn, N. (2007). Relationship-specificity, incomplete contracts and the pattern of trade. *Quarterly Journal of Economics*, 122(2), 569–600.
- Olley, G. S., & Pakes, A. (1996). The dynamics of productivity in the telecommunications equipment industry. *Econometrica*, 64(6), 1263–1297.
- Pages, C., Pierre, G., & Scarpetta, S. (2009). *Job creation in Latin America: Recent trends and policy challenges*. Washington, DC: World Bank.
- Pavcnik, N. (2002). Trade liberalization, exit, and productivity improvements: Evidence from Chilean plants. *Review of Economic Studies*, 69(1), 245–276.
- Petrin, A., & Levinsohn, J. (2012). Measuring aggregate productivity growth using plant level data. *The Rand Journal of Economics*, 43(4), 705–725.
- Prichett, L. (2006). Does learning to add up add up? The returns to schooling in aggregate data. In E. Hanushek, F. Welch (Eds.), *Handbook of the economics of education* (Vol. 1). North Holland.
- Raddatz, C. (2006). Liquidity needs and vulnerability to financial underdevelopment. *Journal of Financial Economics*, 80(3), 677–722.
- Rajan, R. G., & Zingales, L. (1998). Financial dependence and growth. *American Economic Review*, 88, 559–586.

- Restuccia, D., & Rogerson, R. (2008). Policy distortions and aggregate productivity with heterogeneous plants. *Review of Economic Dynamics*, 11(4), 707–720.
- Restuccia, D., & Rogerson, R. (2013). Misallocation and productivity. *Review of Economic Dynamics*, 16(1), 1–10.
- Sarriera, J. M., Serebrisky, T., Araya, G., Briceño-Garmendia, C., & Schwartz, J. (2013). *Benchmarking container port technical efficiency in Latin America and the Caribbean*. IDB Working Paper Series 474.
- Sianesi, B., & Van Reenen, J. (2003). The returns to education: Macroeconomics. *Journal of Economic Surveys*, 17, 157–200.
- Straub, S. (2008). *Infrastructure and growth in developing countries: Recent advances and research challenges*. World Bank Policy Research Working Paper 4460.
- Syverson, C. (2004). Product substitutability and productivity dispersion. *Review of Economics and Statistics*, 86(2), 534–550.
- Syverson, C. (2008). Markets: Ready-mixed concrete. *Journal of Economic Perspectives*, 22(1), 217–234.
- Syverson, C. (2017). Challenges to mismeasurement explanations for the US productivity slowdown. *Journal of Economic Perspectives*, 31(2), 165–186.
- Van Biesebroeck, J. (2008). Aggregating and decomposing productivity. *Review of Business and Economics*, 53(2), 122–146.
- Vandenbussche, J., Aghion, P., & Meghir, C. (2006). Growth, distance to frontier and composition of human capital. *Journal of Economic Growth*, 11(2), 97–127.
- Yu, M., Ye, G., & Qu, B. (2013). Trade liberalisation, product complexity and productivity improvement: Evidence from Chinese firms. *The World Economy*, 36(7), 912–934.