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Corporate Market Power in Romania

Assessing Recent Trends, Drivers, and Implications for Competition

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Abstract

This paper explores firm-level heterogeneity to identify the underlying drivers of market power trends in Romania and the implications for competition and economic growth. The results show that the (sales-weighted) average markup in Romania increased by around 15 percent between 2008 and 2017. A key driving force behind this aggregate trend was the ability of a small fraction of firms—the top decile firms in the markup distribution—to increase their markups. These firms do not seem to follow the typical superstar firms' profile: they are smaller, less efficient, and less likely to invest in intangible assets than other firms in the markup distribution and overrepresented in less knowledge-intensive service sectors (for example, the retail and trade sector). This suggests that the increase in markups in Romania might be associated with an environment that is less conducive to competition. A decomposition exercise shows that the increase in aggregate markups has been driven mostly by incumbents rather than new entrants and exiting firms, which could be interpreted as a sign of consolidation of market power among existing firms. The paper also finds that certain firm characteristics matter to explain differences in markup performance: size, age, research and development profile, export propensity, location, and especially ownership. Further, the paper shows that additional productivity dividends are associated with increased competition in Romania. Overall, these findings illustrate potential policy angles that need to be tackled to enhance market contestability and boost productivity growth, such as addressing regulations that restrict entry and rivalry in the retail trade sector, which concentrates a substantial proportion of high-markup firms, as well as promoting competitive neutrality across markets where public and private actors compete.

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Corporate Market Power in Romania: Assessing Recent Trends, Drivers, and Implications for Competition*

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1. INTRODUCTION AND MOTIVATION

A key stylized fact that has emerged in recent years is that corporate market power has increased at the global level. Drawing upon different methodologies, empirical literature produced in the past 10 years indicates that average levels of market power have been increasing across countries, in both developed and emerging economies. This trend has been measured through different metrics of market power, such as industry sales concentration ratios, firm-level profit rates, or firm-level price-cost margins. For instance, Grullon, Larkin, and Michaely (2018) show that concentration and profit rates have increased across most US industries. De Loecker, Eeckhout, and Unger (2020) estimate firm-level price–marginal cost markups in the United States and find evidence that the revenue-weighted average markup climbed from about 1.2 in 1980 to 1.6 in 2014. De Loecker and Eeckhout (2018) apply the same methodology for a sample of 134 countries and find that revenue-weighted markup has been on the rise for decades not only in the United States but also in Europe, and (to a lesser extent) in emerging economies in Latin America and Asia. Díez, Leigh, and Tambunlertchai (2018) estimate firm-level markups for publicly traded firms in 74 countries between 1980 and 2016, including both advanced and emerging market economies. They find evidence that increased markups are widespread but are more prominent among advanced economies that experienced a 39 percent increase in GDP-weighted average since 1980. More recently, IMF (2019) used firm-level data (including both publicly listed and privately held companies) across 27 countries—16 advanced and 11 emerging markets—to estimate firm-level markups between 2000 and 2015. Results indicate that the average markup for the entire sample of countries moderately increased by around 6 percent across the period studied. The rise was strongly concentrated among advanced economies, but less so among emerging economies (7.7 percent versus 1.8 percent, respectively).

This trend has triggered an intense public debate about market power and its macroeconomic implications. Several authors have tried to link the evidence of rising market power with recent macroeconomic trends, such as the declining share of income and sluggish investment rates.[1] For instance, Barkai (2020) documented a negative industry-level relationship between changes in labor share of income and changes in concentration for the US nonfinancial corporate sector during the period 1984–2014. Autor et al. (2017) find consistent evidence using firm-level data from the US Economic Census between 1982 and 2012, and show that the increase in the concentration of sales experienced in six large sectors of the economy is associated with a decrease in the labor share of value added. Still looking at US sectors but using data from publicly traded firms (through Compustat), De Loecker, Eeckhout, and Unger (2020) find evidence that an increase in markups (aggregated for the whole economy or at the firm level) is negatively correlated with labor share. Other authors focused their analyses on corporate investment rate performance and how it is related to increases in corporate market power. In this regard, Gutiérrez and Philippon (2017a, 2017b) present evidence that increasing market power—captured by rising concentration of industry sales—partly explains the low investment rates experienced by the US economy since the 2000s. IMF (2019) expands the analysis beyond the United States and runs a cross-country firm-level

[1] In principle, several factors—besides rising market power—can contribute to these trends. Potential explanatory factors behind declining investment rates include credit constraints, weakening demand, and a shift in the composition of investment toward intangibles. See Gutiérrez and Philippon (2017a) and Crouzet and Eberly (2018) for a discussion on this matter.

analysis, covering both advanced and emerging economies, to explore the link between markups and physical capital investment and to estimate the extent to which the worldwide average increase in firms' markups experienced since 2000 is associated with a 0.4 percentage point decrease in the investment rate.

Different strands of empirical literature emphasize distinct—but not necessarily exclusive—underlying mechanisms to explain the overall rise in market power. On the one hand, authors such as Autor et al. (2017), Van Reenen (2018), and Bessen (2017) present results that support the hypothesis that increases in market power have been accompanied by efficiency gains. As such, changes in the economic environment—caused by high-tech digital markets engaging in platform competition, increases in investment in intangible capital by leading companies, and scale-biased technical change provoked by advances in information and communication technology (ICT)—have led to the emergence of large, efficient firms. Such so-called superstar firms per Autor et al. (2017) are able to secure larger market shares in "winner takes most" markets.[2] In other words, tougher competition (and not less) in these types of markets would reallocate more output toward the high-markup, larger, and more productive firms. In this context, superstar firms extract a larger market share, which would then explain increases in aggregate (weighted average) market power. On the other hand, some authors argue that the increase in market power reflects declining competition caused by weakened antitrust enforcement or more stringent regulations that lead to worse allocative efficiency. For instance, Gutiérrez and Philippon (2018) argue that weaker antitrust enforcement in the United States relative to the European Union (EU) explains why market power has risen more in the United States than in EU countries.

Against this backdrop, this paper presents new evidence regarding the evolution of corporate market power in Romania. It goes beyond the average performance of firms and explores firm-level heterogeneity to identify the underlying drivers of aggregate market power trends and the implications for economic growth. This paper will explore several questions. At the aggregate level, the following queries will be assessed: Has corporate market power increased? How do aggregate trends differ across sectors, and across technology intensity and knowledge intensity of sectors? Next, the analysis will focus on firm-level drivers of aggregate market power trends. Regarding the latter, the following questions will be assessed: Is variation of market power uneven across firms? To what extent has firm dynamism—through incumbents and new entrants or exiting firms—been driving markup? Does markup performance differ across firms with different attributes? Finally, to account for economic growth implications, the paper will shed light on the potential productivity dividends stemming from fiercer competition across the economy, proxied by a reduction in market power.

2. Methodology

The definition of market power is well established. Taking output markets as the reference point, the standard (theoretical) definition of market power is the ability of a firm to maintain prices above marginal cost, which is the level that would prevail under perfect competition. The exact magnitude of a firm's market power—which is tied to the gap between its price and

[2] According to this view, the dominance of "superstar firms"—such as Amazon, Apple, Facebook, Google, and Microsoft—would be due to intensified competition "for the market" rather than anticompetitive mergers or collusion "in the market" (Van Reenen 2018).

marginal cost—would depend on the format of the residual demand curve faced by the firm; the steeper the inverse demand, the larger the price-cost margin difference, the higher the market power retained by the firm.[3]

However, the actual measurement of market power is not straightforward. A commonly used approach is to approximate market power indirectly through market concentration indicators. These indicators can assume various formats, for instance, concentration ratios and the Herfindahl-Hirschman index (HHI). Although these indicators are often relatively easy to compute—especially because they require only data on firm revenues—they have more drawbacks than benefits. First, and as highlighted in the seminal article of Bresnahan (1989), these indicators do not provide an adequate measure of market power in the presence of product differentiation. Second, the computation of these indicators requires the definition of a relevant market, which usually considers the degree of product substitution, geographic location of both producers and consumers, transportation costs, and so on. In this regard, it is often harder to define markets in periods of technological change. Third, the interpretation of results using these indicators can be ambiguous. As highlighted by Shapiro (2018), an increase in market concentration could indicate a decline in competition, reflecting the existence of less numerous and weaker rivals to dominant incumbent firms; on the other hand, an increase could equally reflect market competition forces in action, making more efficient firms gain larger market shares.

Another way to measure market power is to estimate markups. Markups capture the ability of firms to charge prices above marginal cost. Data availability is the key challenge associated with this methodological alternative, as price data at the firm level rarely are accessible, let alone data on marginal costs.

A common method to estimate markups is the demand approach, which involves estimating a demand system and then adding some assumptions on how firms set prices. The data requirements associated with this approach are significant. The demand method relies on the estimation of a demand system and assumes a fully specified model of consumer choice (see, for instance, Bresnahan 1989). The estimation itself requires detailed data on prices, quantities sold, and product characteristics, all drawing from retail downstream purchases or consumer-level data. Once the own-price and cross-price elasticities across the goods considered are estimated, markups can be recovered from first order conditions after specifying a model of competition. Overall, the main shortcoming of this method is the need to use extremely detailed market-level data. As a result, the approach has been used only to assess market power in specific sectors; for instance, see Berry, Levinsohn, and Pakes (1995)

[3] Following this standard approach, the gap between price and marginal cost could be approximated by a Lerner index, which is calculated as $L_i = \frac{P_i - MC_i}{P_i}$, reflecting how far a firm's price is from its marginal cost. When specifying a demand function, and assuming that firms follow a profit-maximizing behavior, it can be shown that, for a given firm—in a Cournot quantity set case, for instance—the first-order condition equals $L_i = \frac{\alpha_i}{\varepsilon}$, where α_i is the firm's market share and ϵ is the demand elasticity of the firm. Alternatively, in the case of a dominant firm with a competitive fringe that together cover the entire market for a homogeneous good, the Lerner index would be approximated as $L_i = \frac{S_i}{\varepsilon_d + (1 - S_i)\varepsilon_r}$, where ε_d is the market's elasticity of demand, ε_r is the rival's collective elasticity of supply, and S_i denotes the dominant firm's market share.

as well as Berry, Levinsohn, and Pakes (2004) for cars and, more recently, Koujianou Goldberg and Hellerstein (2012) for beer.

The production approach, on the other hand, offers more flexibility. It relies on simpler assumptions and the data requirements are less rigorous: only firms' financial statements are needed. Specifically, there is no need to make assumptions on how firms compete in the market; there are no restrictions on underlying consumer demand, and only firm production data (on inputs and outputs) are needed, which can be easily extracted from firms' financial statements. This methodology—formally presented in De Loecker and Warzynski (2012)—builds on the work of Hall (1988), who shows that under cost minimization, a firm's markup (price over cost) equals the ratio of two values: the output elasticity of a variable input (free of adjustment costs, as opposed to quasi-fixed inputs) and the share of expenditures with that input in total revenue; that is

$$\mu = \frac{\beta_V}{share_V},$$

Where μ is the markup, β_V is the elasticity of output with respect to the variable input, and $share_V$ is the share of revenue spent on the variable input. That said, only two pieces of information are needed to estimate the firm's markup: the output elasticity, which is obtained by estimating a production function of the sector where the firm operates, and the revenue share, which is directly observed in the data.[4]

Given its flexibility, the production approach will be applied to estimate firm-level markups as a proxy for market power in Romania. The implementation of this method follows two steps. The first is to define and estimate a production function to reflect the technology firms have access to. For estimation purposes, a firm's i that belongs to sector j (defined at the NACE 2-digit level) production function at year t is represented by a flexible translog technology as follows:

$$\begin{aligned} y_{jit} = {} & \alpha_{1,j} m_{jit} + \alpha_{2,j} l_{jit} + \alpha_{3,j} k_{jit} + \alpha_{4,j} m_{jit}^2 + \alpha_{5,j} l_{jit}^2 + \alpha_{6,j} k_{jit}^2 \\ & + \alpha_{7,j} m_{jit} l_{jit} + \alpha_{8,j} m_{jit} k_{jit} + \alpha_{9,j} l_{jit} k_{jit} + \alpha_{0,j} + \omega_{jit} + \varepsilon_{jit} \end{aligned}, \tag{1}$$

where all the variables are in natural logarithms and y_{jit} is the firm's annual total revenue from operations, m_{jit} is the total expenditure in intermediate materials, k_{jit} is the capital stock (sum of tangible and intangible assets), and l_{jit} is the total number of hours worked per year (the natural logarithm of the product of the number of employees times the number of months worked times the number of hours worked per month).

TFPR is identified as any change in firms' revenue not caused by variations in the inputs of production. More specifically, in equation (1) TFPR (in natural logarithm) is identified by

[4] The intuition behind this markup measure is discussed in De Loecker (2011). For a cost-minimizing producer, the output elasticity of a variable input equals its expenditure share in total revenue only when price equals marginal cost. Any departure from the perfect competitive model will be captured by the difference between the output elasticity and the revenue share, as measured by the markup (price over cost).

$$\ln TFPR_{jit} = \alpha_{0,j} + \omega_{jit} + \varepsilon_{jit}. \tag{2}$$

The term ω_{jit} is known by the firm, but not by the econometrician, which generates a problem of simultaneity between the inputs and productivity. The last term (ε_{jit}) is assumed to be a completely random productivity shock not anticipated by the firms when making their input choices. The Ackerberg, Caves, and Frazer (2015) approach is followed to solve the endogeneity problem, and the anticipated productivity shock is divided into two terms,

$$\omega_{jit} = g(\omega_{jit-1}) + \xi_{jit}, \tag{3}$$

where the first term, $g(\omega_{jit-1})$, is the inertia of the productivity process; that is, highly productive firms at $t-1$ will also have a high productivity level at t (present).[5] This is the term that firms know when making their input choices. The second term, ξ_{jit}, is the innovation of the productivity process, and it is the key of the estimation process. It can be interpreted as any change in the level of productivity that is completely new at time t and uncorrelated with past productivity.

Since the innovation is uncorrelated with past productivity, it is also uncorrelated with the optimal choices of the variable inputs, that is, materials and labor, made at moment *t−1*. Moreover, since capital is a fixed input, and it takes time to change its level, one can also assume that the innovation of productivity is uncorrelated with the capital input choices made at moment t. This set of assumptions allows one to form a set of moment conditions as follows:[6]

$$E(\xi_{it} l_{it-1}) = E(\xi_{it} m_{it-1}) = E(\xi_{it} k_{it}) = 0, \tag{4}$$

which states that we can use the lack of correlation between lagged flexible inputs and contemporaneous capital, on the one hand, and productivity innovation on the other to identify (estimate) the parameters of the production function in equation (1). To account for differences in production technologies across sectors, the TFPR estimation, as discussed above, allows for heterogeneous sector-specific (NACE 2-digit) production functions.

Using the estimations of the production function, it is possible to compute the output elasticity of the variable input (here assumed as materials) in sector *j* where firm *i* operates, as follows:

$$\hat{\beta}_{M,j} = \frac{1}{N_j} \sum_{\forall i \in j} \left(\hat{\alpha}_{1,j} + 2\hat{\alpha}_{4,j} m_{jit} + \hat{\alpha}_{7,j} l_{jit} + \hat{\alpha}_{8,j} m_{jit} \right). \tag{5}$$

In this regard, it should be noted that all firms in the same sector j are assigned a common elasticity. The interpretation is that firms in the same sector have access to the same technology, but they differ both in terms of $TFPR_{jit}$ and the optimally chosen level of variable input (material).

[5] Following the terminology used in the literature, the current analysis assumes that productivity follows a first-order Markov process in the sense that it depends only on its own past values. The functional form is approximated by a polynomial of degree 3 on the first lag of TFPR. This is a quite general procedure; see for instance, De Loecker (2013).

[6] A moment condition is a statistical equality that holds in the population under study.

Once the output elasticity of the variable input is estimated, the second operational step is to use information on expenditures on variable inputs to compute a firm's markup. Specifically, firm's markup can be directly computed as follows

$$\mu_{jit} = \frac{\widehat{\beta}_{M,j}}{Mshare_{jit}}, \tag{6}$$

where $\hat{\beta}_{M,j}$ was estimated in the previous step and $Mshare_{jit}$ is the ratio of cost of variable input (materials) to corrected revenue defined as:

$$Mshare_{jit} = \frac{P^M M_{jit}}{\left(Y_{jit} / \exp(\varepsilon_{jit}) \right)}, \tag{7}$$

where $P^M M_{jit}$ is total cost of raw materials, Y_{jit} is total revenue, and ε_{jit} is the unanticipated productivity shock, obtained as a residual in the estimation of the production function (see equation 2).

The interpretation of firm-level markups estimated through this production approach must be made with some caution. First, because markup is recovered through TFPR (and not TFPQ) , the estimated result conflates market power itself with differences in product quality and other factors affecting the demand for the product.[7,8] Second—and this applies to any methodological procedure, not only the production approach—markup cannot be taken as an absolute value and should not be used to compare different markets, since markups will be naturally higher in markets where a large proportion of costs are fixed. In this regard, it is safer to use markup estimates to illustrate comparisons across firms within markets, for instance, to shed light on the correlation with other firm characteristics (such as productivity, ownership, size, and location).[9] Last but not least, it is important to stress that rising markups do not necessarily imply a decline in competition. It can reflect vertical differentiation strategies (such as quality upgrading or advertising), or even the implementation of more efficient production processes (or the introduction of innovative products), for which rising markups enable firms to recoup growing fixed costs or to reward high-risk activities, such as investment in R&D. In this context, an in-depth competition assessment would be needed not only to better understand the intrinsic market features (including supply-side and buyer characteristics), but also to identify and assess the potential anticompetitive effects of government intervention in markets.

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[7] To mitigate this conflation risk, the analysis tries, to some extent, to disentangle the sources of markup differences within a sector—that is, whether they are derived from higher prices or lower marginal costs (reflected by higher productivity). This is possible because the procedure adopted generates estimates of both TFPR and markup. See the results in table A1.6 in annex 1.

[8] In a recent article, Bond et al. (2020) argue that in the absence of information on output quantities to estimate TFPQ, as is typically the case (including in the current analysis), it is not possible to obtain consistent estimates of output elasticities when firms have market power and markups are heterogeneous. This issue casts doubt over interpretation of markup values, especially trends. However, the production approach for estimating markups is still valid if results are used to assess differences in average markups across different groups of firms (different characteristics), provided one is willing to assume that these groups of firms share the same production function parameters.

[9] See footnote 8.

3. DATA SET

The assessment of corporate market power in Romania draws on firm-level data from the Structural Business Survey (SBS) for the period 2008–17. The SBS data set—provided by the National Institute of Statistics of Romania—encompasses complete financial information at the headquarters level for the 2008–17 period for the surveyed firms. This survey is exhaustive for firms with at least 20 employees and provides a representative sample for firms with fewer than 20 employees. As such, the data set has two strata: one completely enumerated covering a census of all enterprises with at least 20 employees; and the second, a random stratum, covering some smaller firms. On the basis of this sample design, an unbalanced panel is constructed by considering all listed firms (of both strata) for all years. In this way, the panel allows entry and exit and does not impose any firm size threshold.

Firm-level information from SBS is classified at NACE 4-digit level, which is considered a proxy for the product market where a firm operates. SBS-sampled activities include all sectors except agriculture and banking. Therefore, the analysis focuses on mining, services, and manufacturing activities. In addition, the SBS data assign one NACE 4-digit sector classification for each firm, where the firm's main product is classified. As such, all firms within a NACE 4-digit sector classification are considered to be in one product market. In the current analysis, the *product market* definition deliberately does not coincide with the classical definition of "relevant market,"[10] which normally considers the degree of product substitution, geographic location of both producers and consumers, transportation costs, and so on.[11]

The SBS data contain all the variables needed to estimate the production function that underlies markup computation. The variables needed to estimate TFPR and markups following the production approach—as described in the previous section and expressed in equation (1)—are firms' annual total revenue from operations,[12] total expenditure in intermediate materials, capital stock (sum of tangible and intangible assets), and total number of hours worked per year.

After deflating nominal accounting data and controlling for outliers, the final data set contains 405,641 firm-year markup observations for 167,756 firms over the 2008–17 period. All accounting information from the SBS was deflated, using the country-level GDP deflator (from World Development Indicators and Eurostat), to express values in Romanian lei for 2000. Once nominal values were deflated, additional steps were taken to control for outlier observations; in particular, observations on revenue, employment, capital (tangible assets), and costs of raw materials with a value of zero or lower than zero were excluded from the estimation. This procedure generated a final (unbalanced panel) data set with 405,641 firm-

[10] For market power assessment purposes, a *relevant market* is defined by the set of products and geographical areas that exercise competitive constraints on each other (see Motta 2004 for further discussion).

[11] In principle, this assumption—that firms under one 4-digit sector classification belong to the same market—could imply some bias in the case of multiproduct firms that sell goods that are not close substitutes. However, this bias can be mitigated by using NACE 4-digit sectoral disaggregation. In addition, in the absence of firm-level information for multiple products, it is assumed that the firm-level markup is a weighted average markup across different products within the firm.

[12] The data set does not contain information on physical quantity produced by each firm. Deflated sales are used as a measure of physical quantity to estimate output elasticities and then to recover markups. De Loecker and Warzynski (2012) show that using this approach to recover markups potentially affects the level of estimated markup but not the temporal changes in the markup.

year observations (see table 1), which was then used to estimate markup. The final data set contains firm-year markup observations for 167,756 firms over 2008–17. Table 2 displays the summary statistics for all variables used to compute TFPR and markup for these firms.[13]

[13] The original number of firms in the SBS is 484,604; 405,641 firms were considered after removing outliers in markup and TFPR. This note defines outliers as those observations with a value greater than $Q_3+3*IQR$ or lower than $Q_1-3*IQR$, where Q_1 and Q_3 are the first and third quartiles and IQR is the interquartile range.

Table 1. Final sample of firm-year observations

Year	Manufacturing	Services	Mining	Total
2008	15,056	31,346	320	46,722
2009	14,038	31,598	318	45,954
2010	12,997	29,759	317	43,073
2011	9,492	25,942	239	35,673
2012	10,151	26,983	245	37,379
2013	9,806	29,460	229	39,495
2014	10,381	29,872	253	40,506
2015	10,286	28,844	260	39,390
2016	10,199	28,449	249	38,897
2017	10,018	28,280	254	38,552
Total	112,424	290,533	2,684	405,641

Source: World Bank staff calculations based on SBS data set.
Note: Total number of observations by year and sector with production function variables.

Table 2. Summary statistics

Year	Revenue (ln)		Employment (ln)		Intermediate materials (ln)		Capital stock (ln)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
2008	14.73	2.29	2.89	1.36	12.07	2.67	11.68	2.71
2009	14.70	2.20	2.82	1.32	11.87	2.62	11.82	2.69
2010	14.70	2.28	2.76	1.35	12.02	2.68	11.84	2.68
2011	15.33	2.00	3.06	1.33	12.52	2.60	12.28	2.58
2012	15.23	2.08	3.04	1.32	12.53	2.61	12.22	2.59
2013	15.03	2.12	2.92	1.33	12.32	2.64	12.09	2.63
2014	15.07	2.13	2.94	1.32	12.37	2.62	12.04	2.64
2015	15.32	1.98	3.07	1.28	12.55	2.55	12.11	2.64
2016	15.40	1.91	3.11	1.26	12.44	2.63	12.14	2.63
2017	15.46	1.89	3.13	1.25	12.41	2.70	12.20	2.62
Total	15.08	2.12	2.97	1.32	12.29	2.64	12.03	2.65

Source: World Bank staff calculations based on SBS data set.
Note: SD = standard deviation.

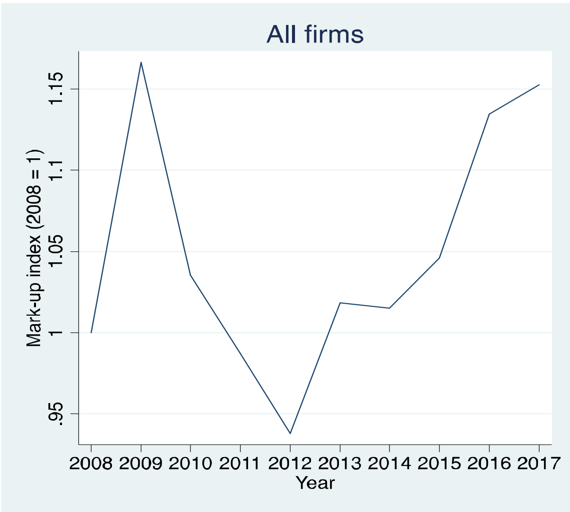
4. Results

4.1. Has corporate market power increased at the aggregate level? How do aggregate trends differ across sectors? Is there a group of firms driving the overall trend?

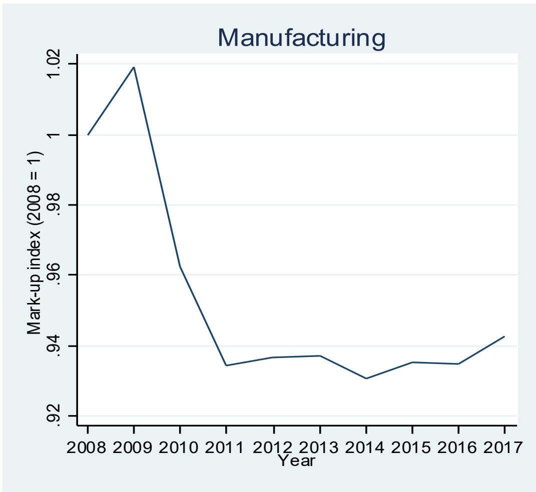
Results show that the average markup in Romania increased by around 15 percent during 2008–17. However, this expansion was marked by an uneven trend. Figure 1, panel a, displays the evolution of the (sales-weighted) aggregate markup for the 2008–17 period for the whole economy (aggregating manufacturing, services, and mining). At aggregate level, average markups experienced a 15 percent aggregate increase from 2008 to 2017. However, three alternating trends are detected in this whole period: a sharp increase of more than 15 percent during 2008–09; a strong decline after 2009, when markups fell by 23 percent from 2009 to 2012; and a consistent increase of 21.5 percent from 2012 to 2017.

Figure 1. Evolution of (sales-weighted) average markup by sector, 2008–17

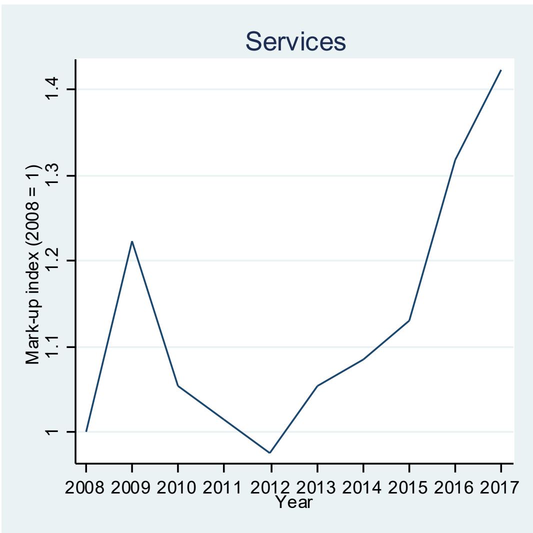
a. All sectors



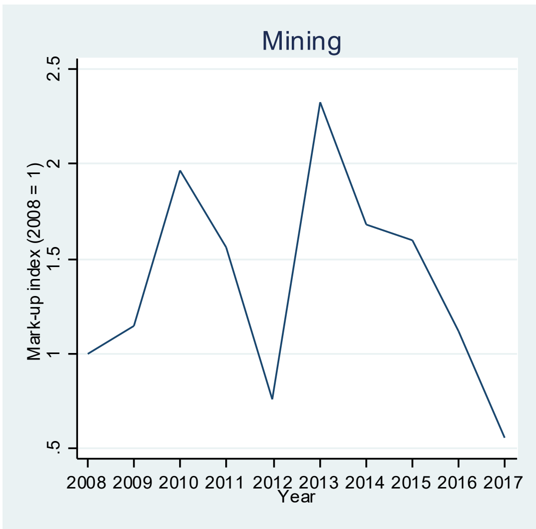
b. Manufacturing



c. Services



d. Mining



Source: World Bank staff calculations based on SBS data set.

Because aggregate numbers mask a lot of heterogeneity, it is not surprising to see

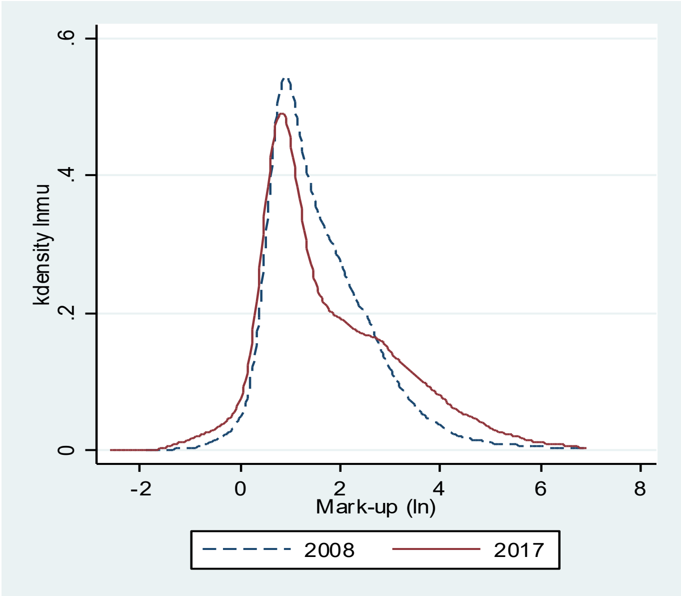
different trends when unraveling markups across sectors. Because of their intrinsic characteristics, firms are different from each other and contrast in terms of performance, even within very narrowly defined sectors (Syverson 2004). These differences could persist either because of supply-side factors, such as management skills, R&D, or investment patterns (Bartelsman and Doms 2000), or because of demand-side factors related to product differentiation, customer-producer relationships, geographical segmentation, among others. That said, firms across high-level sectors—manufacturing, services, and mining—have shown varied performance. While the manufacturing (sales-weighted) average markup experienced a decline of −5.7 percent over the 2008–17 period (figure 1, panel b), there was an opposite, and much more rapid, trend in services, with an aggregate change of 42.2 percent (see figure 1, panel c). Weighted average markup in mining experienced an uneven trend throughout the same period. Nuances are unveiled even within sectors, as aggregate markup performance shows different patterns when breaking manufacturing down into groups of sectors according to their technology intensity.[14] This is also observed when services are broken down into groups of sectors according to their knowledge intensity[15] (see figure A1.1 and figure A1.2 in annex 1).

Further, there is also evidence of changes in the markup firm distribution from 2008 to 2017, revealing an increasing proportion of firms with relatively high markups. Figure 2 displays the firm-level distribution of markups in 2008 and 2017. Some changes are noteworthy. First, both the mean and variance increased over that period. But more importantly, the upper tail of the distribution became fatter over time suggesting that in 2017, more firms have higher markups than in 2008. This suggests that the rise in average markups is associated with large increases among the firms with the highest markups.

[14] As per Eurostat classification, manufacturing sectors are classified as high-technology, medium-high-technology, medium-low-technology, and low-technology, according to technological intensity (R&D expenditure or value added), and based on the statistical classification of economic activities in the European Community (NACE) at the 2-digit level. See table A1.1 in annex 1, with sector aggregation.

[15] As per Eurostat classification, service sectors are classified as knowledge-intensive services (KIS) and less-knowledge-intensive services (LKIS). KISs comprise knowledge-intensive market services, high-tech knowledge-intensive services, knowledge-intensive financial services, and other knowledge-intensive services; LKIS comprise less-knowledge-intensive market services and other less-knowledge-intensive services. Both KIS and LKIS are based on the share of tertiary educated persons at the NACE 2-digit level. See table A1.2 in annex 1, with sector aggregation.

Figure 2. Distribution of firm-level markups, all sectors, 2008 and 2017

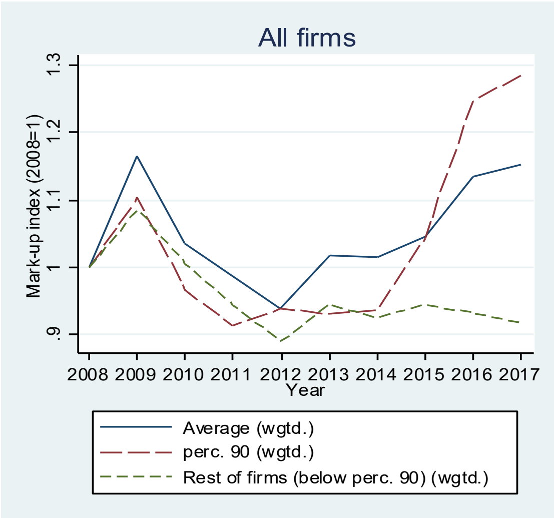


Source: World Bank staff calculations based on SBS data set.

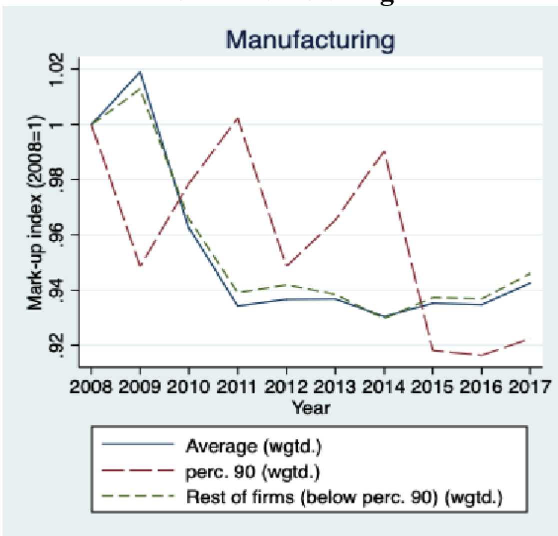
In fact, data show that the rise in average markup has been driven by the ability of a small group of firms—the top decile firms—to increase their markups over time, especially after 2014. Figure 3, panel a, shows that markup growth has been progressively uneven across firms, with firms in the top decile of the markup distribution increasing their average markup faster than the rest of firms. Firms in the 90th percentile increased their (sales-weighted) average markup by 28.5 percent from 2008 to 2017, while the rest of firms—those below the top decile—experienced a completely opposite trend: their weighted markup contracted by 8.3 percent over the same period. This shows that the increase in the weighted average markup—of around 15 percent, as shown in figure 3, panel a—comes mainly from the group of firms in the top decile of the markup distribution. The divergence between the top decile and the rest of firms remains even when results are broken down by sectors; it is more pronounced in manufacturing, despite some volatility (figure 3, panel b), while in services this happens only after 2014 (panel c). The mining sector experienced the opposite trend (panel d), as most of the time (until 2016), the top decile group of the markup distribution reported lower markup growth than the rest of the firms in the data set.

Figure 3. Evolution of (sales-weighted) average markup by sector and by top decile and firm groups (top decile firms versus the rest), 2008–17

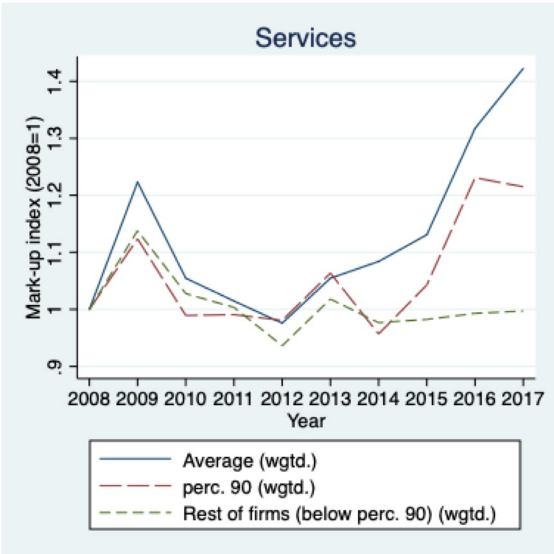
a. All sectors



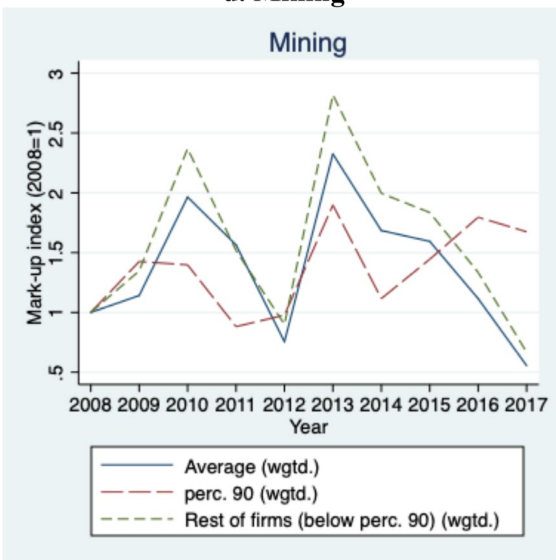
b. Manufacturing



c. Services



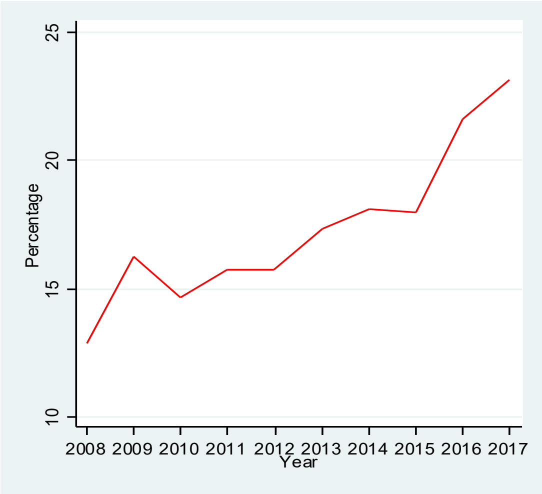
d. Mining



Source: World Bank staff calculations based on SBS data set.

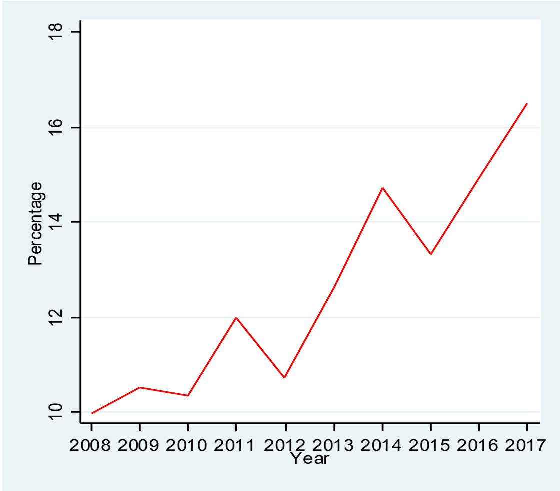
Overall, these results suggest that any analysis about markup performance in Romania should pay attention to a small group of firms: the top decile of firms based on markup distribution. These firms have been accounting for increasing shares of value added and employment in the economy. Figure 4 shows that the share of value added in the whole economy (including manufacturing, services, and mining sectors), as accounted for by the firms in the top decile of the markup distribution, has been increasing, jumping from less than 13 percent in 2008 to 23.1 percent in 2017. The same applies to employment: the sample of the top decile of firms accounts for an increasing share of employment generated in the economy across the 2008–17 period (figure 5).

Figure 4. Share of total value added accounted for by the top decile firms, 2008–17



Source: World Bank staff calculations based on SBS data set.

Figure 5. Share of employment accounted for by the top decile firms, 2008–17



Source: World Bank staff calculations based on SBS data set.

These top decile firms are also typically smaller, less productive, and less likely to invest in intangible assets than the rest of the firms. As highlighted in the methodological section of this paper, the increase of markups cannot be unequivocally interpreted as a decline in competition in a given market; it can reflect firms' efficiency gains or adoption of quality-upgrading strategies. To explore this aspect, a simple econometric analysis was applied to capture performance differences between the group of firms that is leading the markup increase (the top decile firms) and the rest of the firms, based on the markup distribution. The following specification was adopted:

$$Characteristic_{cjit} = \delta_0 + \delta_1 Top\_decile_{it} + \eta_t + \rho_j + \gamma_c + \mu_{cjit}\,, \qquad (8)$$

where the dependent variable reflects different firm characteristics (of firm *i* that operates in sector *j,* county *c,* at year *t*) to be compared. Three dependent variables are tested: size (measured in terms of the number of full-time employees), productivity (measured as TFPR discounted for markup[16]), and intangible assets (measured as a dummy that takes the value of 1 for firms having a positive value of intangible fixed assets[17]). The key explanatory variable is Top_decile_{it}, a dummy that takes the value of one firm if *i* is among the top decile of the markup distribution in year *t*—while η_t, ρ_j, and γ_c are, respectively, time, NACE 4-digit sector, and county fixed effects. The parameters of equation (8) are estimated by OLS (or Probit regression maximum likelihood, when the dependent variable is the intangible assets dummy), always using heteroscedasticity-robust standard errors. Results displayed in table 3, columns 1 and 2, suggest that firms in the 90th percentile of the markup distribution are, on average, 46.8

[16] TFPR discounted for markup is computed as TFPR-markup. In this regard, it is not a perfect measure of the true technical efficiency, but just a proxy of productivity that accounts for market share and the effect of materials elasticity, while other factors, such as the effect of product quality or innovation, are not considered.
[17] Value of intangible assets in the SBS data set is defined as value built on (a) R&D expenditure and (b) franchise, patents, and other similar rights and values.

percent[18] smaller and 91 percent [19] less productive than the rest of the firms, even within narrowly defined sectors (at NACE 4-digit level). Results in column 3 captures the differences between these two groups of firms in terms of their willingness to invest in intangible assets—their "knowledge capacity"—a key determinant of firms' expansion in the long term. Results suggest that the sample of top decile firms are almost 33 percent less likely to invest in intangible fixed assets than the remaining firms, even within NACE 4-digit sectors.[20] All these correlations are statistically significant at the 1 percent confidence level.

Table 3. Characteristics of top decile firms: Conditional correlations between markups and firm characteristics (OLS and Probit results)

	(Estimation method) Dependent variable		
	(1) (OLS) Employment (ln)	**(2) (OLS) TFPR discounted for markup (ln)**	**(3) (Probit) Investment in intangibles (yes/no)**
Top _decile	−0.632***	−2.422***	−0.386***
NACE 4-digit sector fixed effects	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
R^2 (pseudo R^2)[a]	0.238	0.728	0.078
Observations	484,604	403,561	484,594

Source: World Bank staff calculations based on SBS data set.
Note: All firm-year observations (for the 2008–17 period) are pooled together, and NACE 4-digit sector and year fixed effects are included. OLS = ordinary least squares; TFPR = revenue-based total factor productivity.
a. It is worth highlighting that R^2 value does not influence the consistency of the estimators of each population parameter, which is the objective of the current analysis. See, for instance, Cameron and Trivedi (2010) for a theoretical discussion on this matter. Moreover, since the analysis draws on a large sample, the standard errors of the coefficient estimators are not affected because of the law of large numbers. The key issue would be the lack of correlation of omitted variables and the explanatory variables. However, given that the main (theoretical) determinants of the markup performance are included, the omitted variables can be understood to be random.
*** Statistically significant at 1 percent.

In addition, the group of 10 top decile firms in the markup distribution operate mainly in the services sector and are overrepresented in less-knowledge-intensive services sectors, with some exceptions. Table 4 displays the distribution of top decile firms across NACE 2-digit sectors in 2017. To control for the fact that some sectors might be overrepresented (given the SBS survey sampling), the table shows only those sectors for which the probability of a firm being in the top decile is larger than the sector's frequency ratio. Results show that firms in the 90th percentile of markup distribution are overrepresented in wholesale trade and retail trade sectors; the probability of a top decile firm being in these two sectors—classified as less-knowledge-intensive services, according to the Eurostat definition

[18] This value results from the following expression: 100*[exp(beta)−1], where beta equals estimated top 90 percent dummy coefficients in an OLS regression where size is the dependent variable, controlling for 4-digit and county fixed effects (table 3, column 1).
[19] This value results from the following expression: 100*[exp(beta)−1], where beta equals estimated top 90 percent dummy coefficients in an OLS regression where *TFPR* is the dependent variable, controlling for 4-digit and county fixed effects (table 3, column 2).
[20] The odds-ratio is computed as the relative difference between the marginal effects for each category (that is, 42 percent for the top decile firms and 56 percent for firms below the 90th percentile). Specifically, it is computed as follows: (56 percent − 42 percent)/(42 percent).

(see table A1.2 in annex 1)—is almost 40 percent.[21] It is worth highlighting, however, that these top decile firms also operate in some knowledge-intensive services sectors, though the probability is much smaller: 3.87 percent for computer programming and 2.68 percent for security and investigating activities.[22]

When taken together, these results suggest that the small group of firms leading the overall increase in markups in Romania does not seem to follow the typical superstar firms' profile. As discussed by Van Reenen (2018) and Autor et al. (2017), superstar firms—typically with higher markups, larger, and more productive – would be rewarded with larger market shares due to their innovative nature. This hypothesis does not seem to be supported by data in Romania. As results showed, the group of firms who are driving the aggregate rise in markups—the top decile firms of the markup distribution—are typically smaller, less productive, less likely to invest in intangible assets, and are mostly active in services sectors where use and diffusion of knowledge is less important. This may suggest that the increase in markups in Romania might reflect a less competition-intensive environment rather than changes in the nature of competition, where superstar firms would be rewarded with greater market share because they are more efficient and innovative.

Table 4. Probability of a top decile firm (in the markup distribution) being in the following sectors

2-digit sector	Probability
Wholesale trade	24.36
Retail trade	14.77
Computer programming	3.87
Manufacturing of wearing apparel	3.21
Real estate activities	3.14
Security and investigation activities	2.68

Source: World Bank staff calculations based on SBS data set.
Note: The table shows only sectors for which the probability of a firm being in the top decile of markup distribution is higher than the sector's overall frequency ratio.

4.2. How have firm dynamics influenced aggregate markup performance? Are there signs of market power consolidation among incumbent firms?

To indirectly assess whether the rise in markups is associated with weakening competition, the analysis decomposes the evolution of aggregate markups into that of incumbents and of net entry of firms. To do so, the Melitz and Polanec (2015) decomposition technique is applied to the aggregate markup changes between 2008 and 2017. This approach follows two steps. First, the aggregate (ln) markup (μ) at year t is defined as

[21] Under the NACE 2-digit wholesale trade sector, the group of top decile firms are overrepresented in the following NACE 4-digit sectors: sector 4690–Non-specialized wholesale trade; sector 4673–Wholesale of wood, construction materials, and sanitary equipment; sector 4621–Wholesale of grain, unmanufactured tobacco, seeds, and animal feeds; sector 4646–Wholesale of pharmaceutical goods; sector 4675–Wholesale of chemical products; and sector 4631–Wholesale of fruit and vegetables. Under the NACE 2-digit retail services sector, the sample of top decile firms are overrepresented in the following NACE 4-digit sectors: sector 4711–Retail sale in non-specialized stores with food, beverages or tobacco predominating; and sector 4730—Retail sale of automotive fuel in specialized stores.

[22] The same analysis is applied for ownership structure, again controlling for overrepresentation. Results show that the sample of top decile firms are overrepresented in the fully foreign-owned ownership category.

$$\mu_{jt} = \sum_{i \in k_j} \sum_{i \in \Omega_t} s_{jit}\, \mu_{jit} \,, \tag{9}$$

where s_{jit} is firm i's market share at moment t, where the market share is defined in terms of firm i's revenue weight over the total revenue of sector j (k_j), where sector j is the sector to which firm i belongs. Then the change of (ln) markup between moments t and $t-1$ is decomposed as

$$\Delta\mu_{jt} = \Delta\bar{\mu}_{S,jt} + \Delta Cov_S(\mu_{S,jit}, s_{S,jit}) + s_{E,jt}(\mu_{E,jt} - \mu_{S,jt}) + s_{X,jt}(\mu_{S,jt} - \mu_{X,jt}) \,, \tag{10}$$

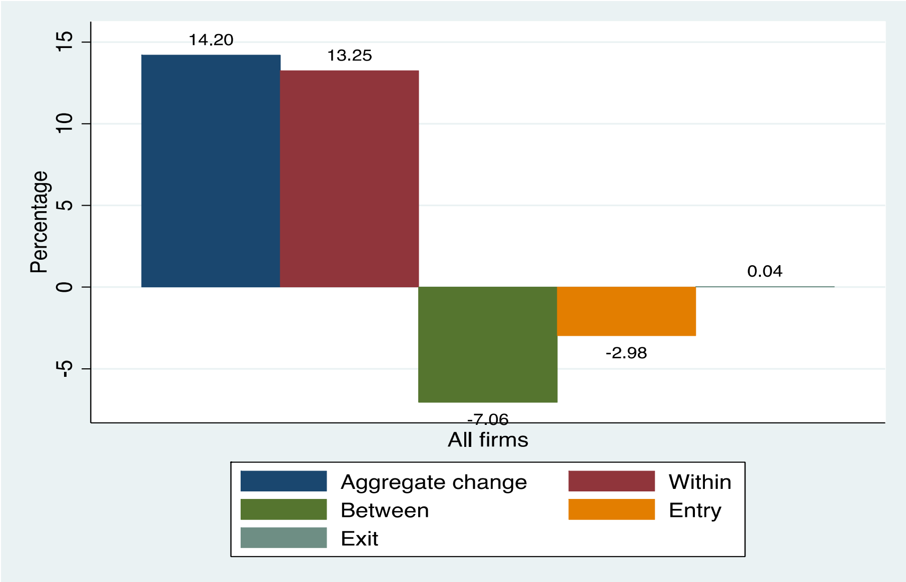
where the subindex $_S$ refers to survivor firms, (that is, those operating in both years t and $t-1$; the subindex $_X$ denotes firms exiting the market, or those firms present in moment $t-1$ but not in moment t; and $_E$ denotes entrants, or those firms operating in moment t but not in moment $t-1$. Each component expressed in equation (10) represents different drivers to explain aggregate change in markup over the period. The first term, $\Delta\bar{\mu}_{S,jt}$, is the change of the unweighted average ln markup of survivors, or the "within" component. Likewise, $\Delta Cov_S(\mu_{S,jit}, s_{S,jit})$ is the change in the covariance between ln markup and market share for survivors only. This is the "between" component, and it measures the reallocation of resources among surviving firms. The term $s_{E,jt}(\mu_{E,jt} - \mu_{S,jt})$ is the "entry" component, and it measures the difference of the aggregate ln markup of entrants and that of survivors at moment t weighted by the share of entrants over the total population of firms ($s_{E,jt}$). The entry component will be positive if the aggregate markup of those firms entering the market is larger than the aggregate markup of the survivors. Finally, $s_{X,jt}(\mu_{S,jt} - \mu_{X,jt})$ is the exit component, which measures the difference between the aggregate ln markup of survivors and exiting firms at moment $t-1$, likewise weighted by the proportion of firms exiting the market, that is, $s_{X,jt-1}$. This term is positive if the aggregate ln markup of the exiting firms is lower than the aggregate ln markup of survivors. In other words, and as displayed in equation (10), aggregate markup can grow/shrink because (a) incumbent firms have increased/decreased their markups (the "within" component), (b) incumbent firms with high markups have gained/lost market share (the "between" component), and (c) entrant firms have higher/lower markups than exiting firms (the "entry" or "exit" component).[23]

Results show that the increase in aggregate markups has been driven mostly by incumbents rather than entrants and exiting firms. Decomposition results for the full sample of firms are displayed in figure 6. Estimations suggest that a large proportion of the aggregate increase in markup in Romania was driven by increases within incumbent firms (the "within" bar). And among incumbents, results show that the rise in markups reflects mostly a markup increase within firms rather than a reallocation of market share away from low-markup to high-markup companies (the "between" bar). Meanwhile, the entry of new firms with lower markups pulled the change in aggregate markups down (the "entry" bar), and contribution from

[23] SBS tends to underestimate entry and exit (populational) figures as a result of its sampling design. In this regard, the proposed analysis captures entry and exit in the enumerated stratum (above 20 employees), so results will be representative at least for the population of firms in the enumerated stratum.

exiting firms was negligible.

Figure 6. Decomposition of percentage change of (sales-weighted) average markup, 2008–17



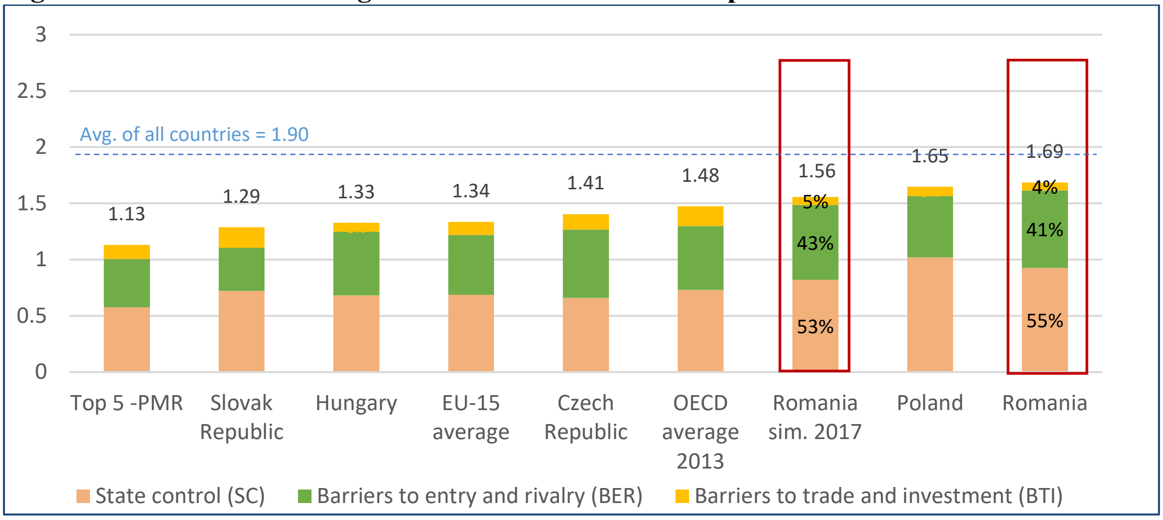
Source: World Bank staff calculations based on SBS data set.

This result could be interpreted as a sign of consolidation of market power among existing firms enabled by remaining product market regulations that restrict competition, despite previous reforms. Several policy-related factors can explain this result, among them, government interventions and regulations that restrict competition by reinforcing dominance or limiting entry, facilitating collusive outcomes or increasing the cost to compete in markets, and discriminating and protecting vested interests.[24] In this regard, Pop and Ore Monago (2020) provide illustrative examples about the presence of regulations that still restrict competition in Romania, drawing from the OECD–World Bank Group (WBG) product market regulation (PMR) indicators data set, which provides information across 70 countries.[25] The assessment uses the latest PMR round for Romania from 2013 and includes Romania's performance projected on the basis of information updated in 2017. Results suggest that the regulatory framework as it is in the books in Romania is less restrictive than that of countries such as Poland and the total sample average, but it is more restrictive than that of the OECD and EU-15 countries. However, from an economywide perspective, the overall restrictiveness of regulations in Romania is mainly associated with the state control of the economy and several remaining barriers to entry and rivalry (see figure 7).

[24] In principle, greater competition outcomes are enabled through an effective competition policy framework, which involves three key pillars: (a) fostering pro-competition regulations and government interventions, (b) promoting competitive neutrality and non-distortive public aid, and (c) enabling effective competition law and antitrust enforcement.

[25] The current PMR database used for this study includes Argentina, Australia, Austria, Belgium, Bolivia, Brazil, Bulgaria, Canada, Chile, China, Colombia, Costa Rica, Croatia, Cyprus, the Czech Republic, Denmark, the Dominican Republic, Ecuador, Arab Republic of Egypt, El Salvador, Estonia, Finland, France, Germany, Greece, Guatemala, Honduras, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Jamaica, Japan, Kenya, the Republic of Korea, Kuwait, Latvia, Lithuania, Luxembourg, Malta, Mexico, the Netherlands, New Zealand, Nicaragua, Norway, Panama, Paraguay, Peru, the Philippines, Poland, Portugal, Romania, the Russian Federation, Rwanda, Senegal, the Slovak Republic, Slovenia, South Africa, Spain, Sweden, Switzerland, Turkey, Tunisia, Ukraine, Uruguay, the United Kingdom, and the United States.

Figure 7. Product market regulation in Romania and comparator countries



Source: Pop and Ore Monago 2020.
Note: The top five performers in the overall PMR indicator are the Netherlands, United Kingdom, Austria, Denmark, and New Zealand. Figure shows 2013 information, unless otherwise indicated. PMR = product market regulation.

Barriers to entry and rivalry still affect some service sectors. In fact, there are examples of regulations that hamper competition in retail trade, which concentrates a substantial proportion of high-markup firms in the Romanian economy, as seen previously. Drawing from the OECD-WBG PMR data set, Pop and Ore Monago (2020) show that although regulations in the retail trade sector are less restrictive than in the EU-15 and OECD, there is still room for improvement to make the retail trade market more efficient. The authors show that licenses and permit requirements may still be imposing an unnecessary burden on entry and increasing the costs to compete in the sector. Companies operating in retail sectors in Romania are subject to requirements that go beyond the general conditions, formalities, and procedures applicable to any company. For instance, in Romania's clothing industry, licenses and permits are always required, compared with 57 percent of OECD countries and 60 percent of EU-15 countries, which do not have such a requirement.[26] In addition, Romania has regulations that impose restrictions on entry or expansion of business activities and constrain strategic options to compete in retail markets. For instance, most of the PMR countries and all top five performers do not restrict firms from selling below cost (beyond a prohibition of predatory pricing), and restrictions on sales promotions are not a common practice either.[27] In Romania, sales below cost are prohibited or restricted beyond a prohibition of predatory pricing. Likewise, sales promotions are restricted to a particular time of the year.[28]

4.3. Do firm markups differ across firms with different attributes?

To answer this question, the analysis explores how markup performance differs across different types of firms. To assess the heterogeneity in markups, the analysis relates markups to firm-level characteristics, such as size, age, ownership status, R&D status, and location,

[26] In this case, the least restrictive countries, such as Bulgaria, Latvia, and Sweden, do not have such requirements.
[27] Among the Central and Eastern Europe comparator countries, only the Czech Republic and the Slovak Republic apply restrictions on discounted sales pricing, while only Poland applies constraints to sales promotions.
[28] Government Ordinance no. 99/2000 prohibits sales below costs and provides for the conditions and periods when certain types of promotions can take occur.

within narrowly defined product markets, proxied by NACE 4-digit sectors. The following regression is estimated:

$$\mu_{cjit} = \delta_0 + \sum_{k=2}^{7} \delta_{1k} own_{k,cjit} + \sum_{r=2}^{3} \delta_{2r} size_{r,cjit} + \sum_{q=2}^{3} \delta_{2q} age_{q,cjit} + \delta_3 d_{cjit}^{Exp} + \delta_4 d_{cjit}^{Rnd} + \delta_5 k_{cjit} + \eta_t + \rho_j + \gamma_c + u_{cjit} \,, \quad (11)$$

where $own_{k,cjit}$ with $k = 2,3,\ldots,7$ comprises a set of dummies defining the type of ownership of the firm, Romanian private (omitted category), majority state-owned, state-private ownership, Romanian private and foreign, fully foreign-owned, public of national and local interest, and other (cooperatives and craft organizations).[29] The term $size_{r,cjit}$ is a set of three dummies controlling for firms' size—small, or fewer than 50 employees (omitted category); medium, or 51–250 employees; and large, more than 250 employees. The term $age_{r,cjit}$ is a set of three age dummies—young, or less than 5 years old; mature, or 6–15 years old; and older than 15 years. Two dichotomous variables are also defined to capture export and R&D profiles: d^{Exp} and d^{Rnd} ,which take a value of 1 if a firm's direct exports represent more than 10 percent of a firm's total revenue and if a firm's R&D represents more than 1 percent of a firm's total revenue, respectively. In addition, k_{cjit} is firms' total capital stock value (sum of tangible and intangible assets).[30] Finally, η_t, ρ_j, and γ_c are, respectively, time, NACE 4-digit sector, and county fixed effects. Equation (11) is estimated separately for each 1-digit sector (that is, manufacturing, services, and mining) and for the whole economy, while the equation parameters are estimated by OLS, always using heteroscedasticity-robust standard errors. The complete set of results is displayed in table A1.5 in annex 1.

Results show that ownership structure matters to explain markup differences across firms. State-controlled companies tend to exert the highest markup premiums in the overall economy and especially in the manufacturing sector. Table 5 displays the estimated coefficients of ownership categories multiplied by 100. Except for the mining sector, most of estimated coefficients are statistically significant, which suggests that ownership structure makes a difference to explain markup performance, even for firms operating in the same product market (here proxied by NACE 4-digit sector), county location, and year, and with similar characteristics in terms of size, age, and export and R&D profile.

In particular, firms in which the state has majority or minority ownership demonstrate higher markups when compared with domestic privately owned companies (see table 5, column 4). The average difference in markup is higher for companies with minority state ownership (28.9 percent) than for fully state-owned companies (20.0 percent). In manufacturing, markups of fully state-owned firms are the highest on average, at 52.7 percent, when compared with the reference category (domestic privately owned firms). Results in services are mixed, with both private and state ownership extracting high premiums: private firms with mixed domestic-foreign ownership show the highest average difference (27.9 percent), closely followed by minority state-owned companies for which the markup premium

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[29] More details about the original ownership classification in SBS, and the aggregation used for the analysis, can be found in table A1.3 and table A1.4 in annex 1.

[30] The variable $\ln TFPR_{kit}$ is included as an additional control to test the robustness of the analysis. See results in table A1.6 in annex 1.

is 27.5 percent, compared with the reference category. [31] All results are robust to the inclusion of productivity as an additional control variable (see results in table A1.6 in annex 1).[32]

Table 5. Average markup differences by ownership structure, relative to domestic, privately owned firms

	(1) Manufacturing (%)	(2) Services (%)	(3) Mining (%)	(4) All sectors (%)
Majority state-owned	52.7	13.9	77.2	20.0
State-private ownership	35.2	27.5	n.s.	28.9
Domestic private + foreign	16.1	27.9	n.s.	22.9
Fully foreign-owned	10.5	26.3	n.s.	20.1
Public of national and local interest	20.9	14.9	n.s.	21.4

Source: World Bank staff calculations based on SBS data set.
Note: Numbers reflect estimated coefficients (multiplied by 100) for ownership dummy categories—relative to Romanian private firms, the omitted category—in a fixed-effect regression model controlling for firm covariates plus year and NACE 4-digit sector fixed effects, as displayed in equation (11). More details about the original ownership classification in SBS, and aggregation used for the analysis, can be found in table A1.3 and table A1.4 in annex 1. See table A1.5 in annex 1 for the complete set of results.
n.s. = not statistically significant.

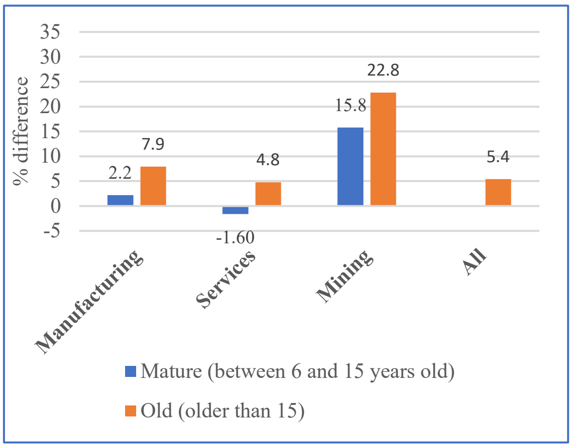
Larger firms and older companies wield higher markups when compared with their counterparts, implying that firm size and age are relevant characteristics that influence markup differences. As shown in figure 8, old companies (older than 15 years) display higher average markups than young ones (1–5 years old), even when they share similar attributes (in terms of ownership structure, size, and export and R&D profiles) and operate in the same NACE 4-digit sector, county, and year. The estimated average markup premium for old companies (relative to young ones) is 5.4 percent for the whole economy. It varies depending on how data are clustered across large sectors: 7.9 percent in manufacturing, 4.8 percent in services, and 22.8 percent in mining. Higher markup premiums for older companies can be interpreted in two ways: it can reflect that more experienced firms are able to transpose learning returns—which could positively affect their productivity or reduce their marginal costs—into higher markups, or that older firms are able to lobby better and create barriers to entry, making it more difficult for younger firms to exert competitive pressure. Firm size also matters to explain markup performance: large companies (with more than 250 full-time employees) tend to display higher markups compared with small companies, even when they operate in the same product market and share similar characteristics. On average, for the whole economy, the

[31] Results for the category "other" are not shown in table 5. As detailed in table A1.3 in annex 1, this "other" category refers to SBS ownership answer-codes 40 and 50: respectively, "cooperative" and "public of national and local interest." The reason the corresponding results were not highlighted in the main text are twofold. First, the above-mentioned category accounts for only 0.06 percent of total companies in the sample. Second, an in-depth analysis would be needed to understand whether this "other" category reflects potential noise in the way firms self-classify their ownership structures or the way firms report cost expenditures (mainly), or whether this was influenced by SBS sampling design.

[32] Because the production approach applied in the current analysis delivers both markup and productivity estimates, it is possible to further decompose the markup differences across firm characteristics, and to verify whether, after controlling for differences in marginal costs (that is, productivity), certain groups of firms still have higher markups. This is precisely one of the mitigating methods employed to reduce the conflation risk, as highlighted before. Results in table A1.6 in annex 1 should be interpreted as follows: once productivity level is included in the equation, differences in marginal cost are accounted for so the coefficient on "majority state-owned," for instance, captures the variation in average prices between majority state-owned and the size reference category (domestic privately owned firms).

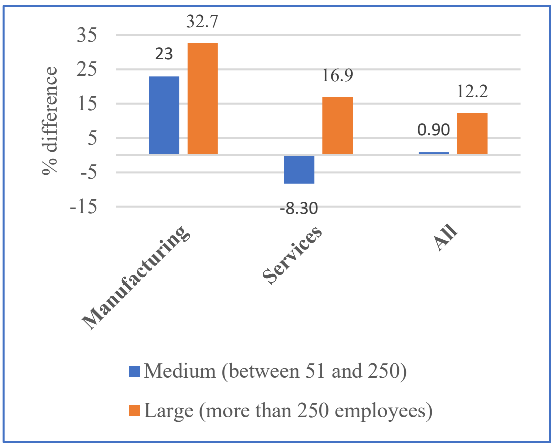
markup premium for large companies is 12.2 percent higher than that of small firms (figure 9). Both size and age effects are still present, even after controlling for productivity differences (see table A1.6 in annex 1).[33]

Figure 8. Average markup differences relative to young firms, by age category



Source: World Bank staff calculations based on SBS data set.
Note: Numbers reflect estimated coefficients (multiplied by 100) for age dummy categories—relative to young firms (1–5 years old), the omitted category—in a fixed-effect regression model controlling for firm covariates plus year, county, and NACE 4-digit sector fixed effects, as displayed in equation (11). All bars reflect statistically significant results. See table A1.5 in annex 1 for the complete set of results.

Figure 9. Average markup differences relative to small firms, by size category

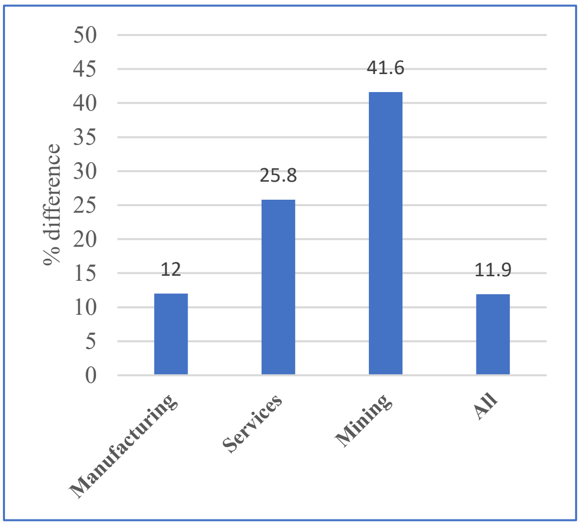


Source: World Bank staff calculations based on SBS data set.
Note: Numbers reflect estimated coefficients (multiplied by 100) for size dummy categories—relative to small firms (1–50 employees), the omitted category—in a fixed-effect regression model controlling for firm covariates plus year, county, and NACE 4-digit sector fixed effects, as displayed in equation (11). All bars reflect statistically significant results. See table A1.5 in annex 1 for the complete set of results.

By the same token, export intensity also influences markup performance, with firms that export earning higher markups. Being an exporter is a relevant firm feature to be analyzed when it comes to understanding markup performance. Recent models of international trade predict that exporting firms earn higher markups than non-exporting firms, either because they are relatively more productive and can thus undercut their rivals (see Melitz and Ottaviano 2008), or because they produce higher-quality goods and rely on higher-quality inputs, which allow them to charge higher prices (see Hallak and Sivadasan 2009). In this regard, the results summarized in figure 10 are consistent with the literature and suggest that exporting firms—defined as those whose direct exports represent more than 10 percent of total revenue—earn higher markups than non-exporting firms that operate in the same product market (NACE 4-digit sector); the difference ranges from 12 percent to 41.6 percent, depending on how data are clustered across large sectors (manufacturing, services, and mining).

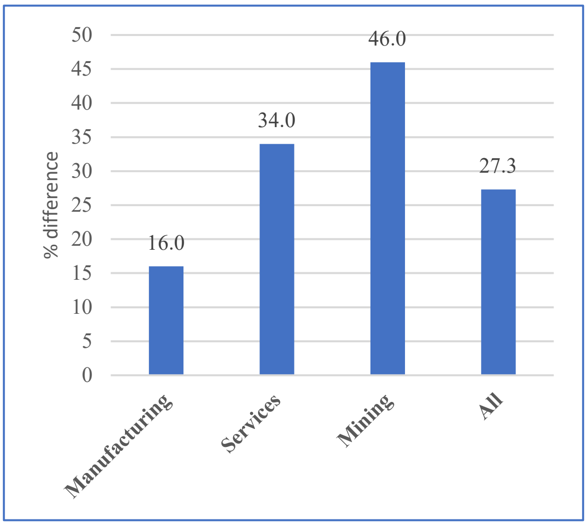
[33] See footnote 32 on how to interpret results in table A1.6 in annex 1 (after including productivity as an additional control).

Figure 10. Average markup differences relative to non-exporters by export status



Source: World Bank staff calculations based on SBS data set.
Note: Numbers reflect estimated coefficients (multiplied by 100) for R&D dummy category—relative to non-R&D performer firms, the omitted category—in a fixed-effect regression model controlling for firm covariates plus year, county, and NACE 4-digit sector fixed effects, as displayed in equation (11). All bars reflect statistically significant results. See table A1.5 in annex 1 for the complete set of results.

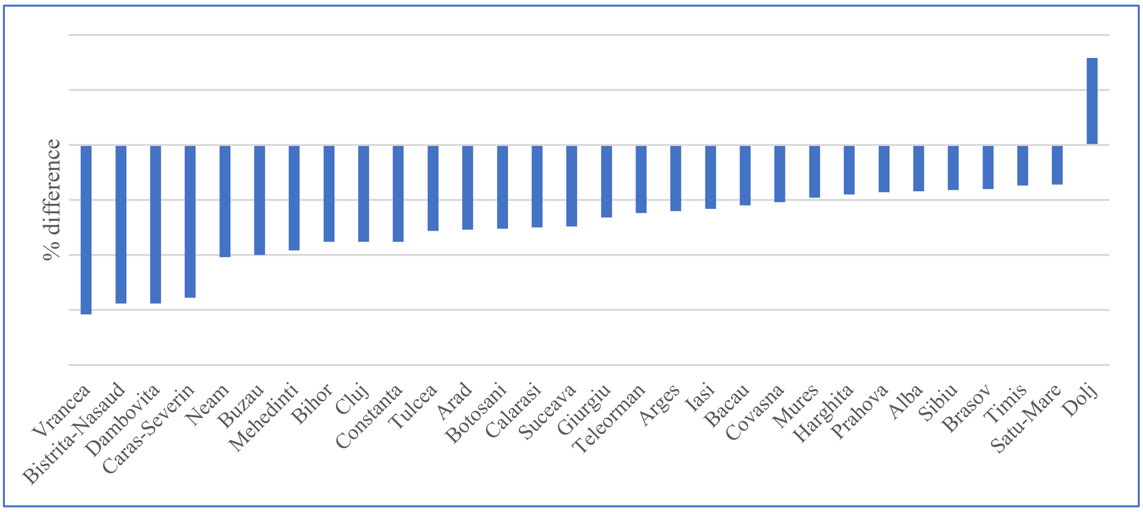
Figure 11. Average markup differences relative to non-R&D performers by R&D status



Source: World Bank staff calculations based on SBS data set.
Note: Numbers reflect estimated coefficients (multiplied by 100) for export dummy category—relative to non-exporters, the omitted category—in a fixed-effect regression model controlling for firm covariates plus year, county, and NACE 4-digit sector fixed effects, as displayed in equation (11). All bars reflect statistically significant results. See table A1.5 in annex 1 for the complete set of results.

Performing R&D activities is positively correlated with markup differences, while location, proxied by county, also matters to explain markup performance. Results displayed in figure 11 show that R&D performers—identified by those firms whose R&D expenses surpass more than 1 percent of their total revenue—tend to earn higher markups than non-R&D performers. The markup premium for R&D performers is always positive, suggesting that this group of firms is able to recoup fixed costs associated with R&D activities. The magnitude of the premium varies from 16 percent to 46 percent, depending how data are clustered across large sectors (manufacturing, services, and mining). In addition, results displayed in figure 12 show that firms in the same product market (at NACE 4-digit level) and with similar characteristics (in terms of ownership, age, size, and export and R&D profiles) charge different markups depending on the county in which they operate. Except for Dolj, firms in all other counties demonstrate lower average markups than Bucharest; the negative markup premium in relation to Bucharest varies from −15.4 percent (Vrancea) to −3.6 percent (Satu-Mare).

Figure 12. Average markup differences by county relative to Bucharest



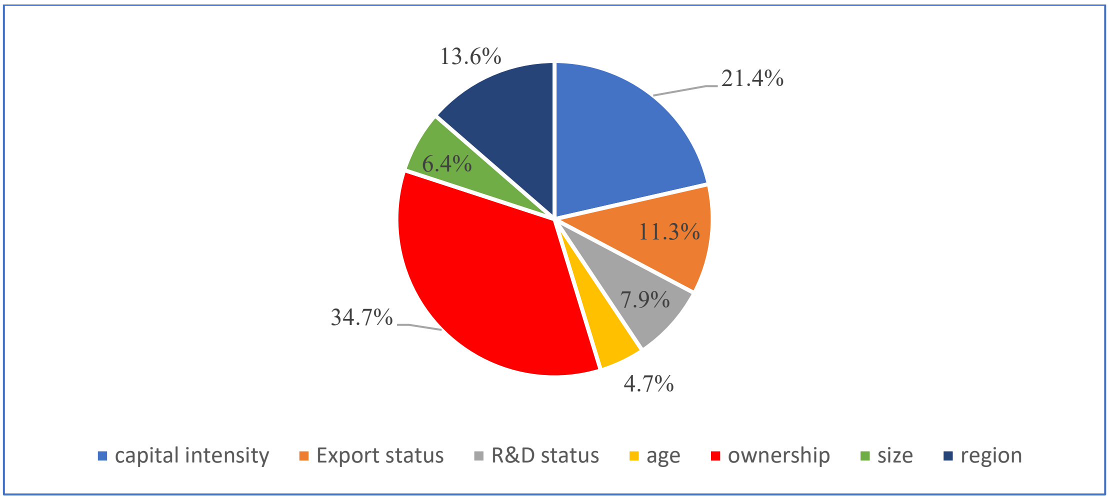
Source: World Bank staff calculations based on SBS data set.
Note: Numbers reflect estimated coefficients (multiplied by 100) for county fixed effects—relative to Bucharest, the omitted category—in a fixed-effect regression model controlling for firm covariates plus year and NACE 4-digit sector fixed effects, as displayed in equation (11). All bars reflect statistically significant results. See table A1.5 in annex 1 for the complete set of results.

A variance decomposition analysis suggests that ownership is the most relevant characteristic to explain total variance of markup performance across firms in Romania, followed by capital intensity and export status. Drawing from estimations of equation (11), it is possible to evaluate the relative importance of each variable to explain the variance of the markup. Letting d^{Exp} represent any of the explanatory variables of equation (11), the contribution to the variance of the markup of that variable can be defined as

$$Cont_{d^{Exp}} = \frac{\delta_3^2 Var(d^{Exp}) + 2\delta_3 Cov(d^{Exp}, \mu - \delta_3 d^{Exp})}{Var(\mu)}, \quad (12)$$

or as the variance of the variable plus 2 times the covariance of the variable, with the part of the markup not explained by that variable. A similar expression can be derived for any of the remaining explanatory variables. The relative contribution of each variable is computed after discounting the residuals, sector, and year contributions. Results are displayed in figure 13. Ownership structure is shown to be the most relevant feature to explain the variance of markup performance across firms: it accounts for 34.7 percent of the explained variance of markup performance (after removing NACE 4-digit sector and year contributions). The second most important characteristic is capital intensity, corresponding to 21.4 percent of the variance of the markup performance. Export status accounts for the third largest share in explained variance: 11.3 percent.

Figure 13. Contribution by each firm characteristic to explain total variance of markup performance across firms



Source: World Bank staff calculations based on SBS data set.
Note: The pie chart reflects markup variance decomposition results. It decomposes the variance of markup performance across firms after removing the proportion accounted for by omitted factors, NACE 4-digit sector, and year contributions.

4.4. WHAT WOULD BE THE PRODUCTIVITY DIVIDENDS FROM MARKUP REDUCTION?

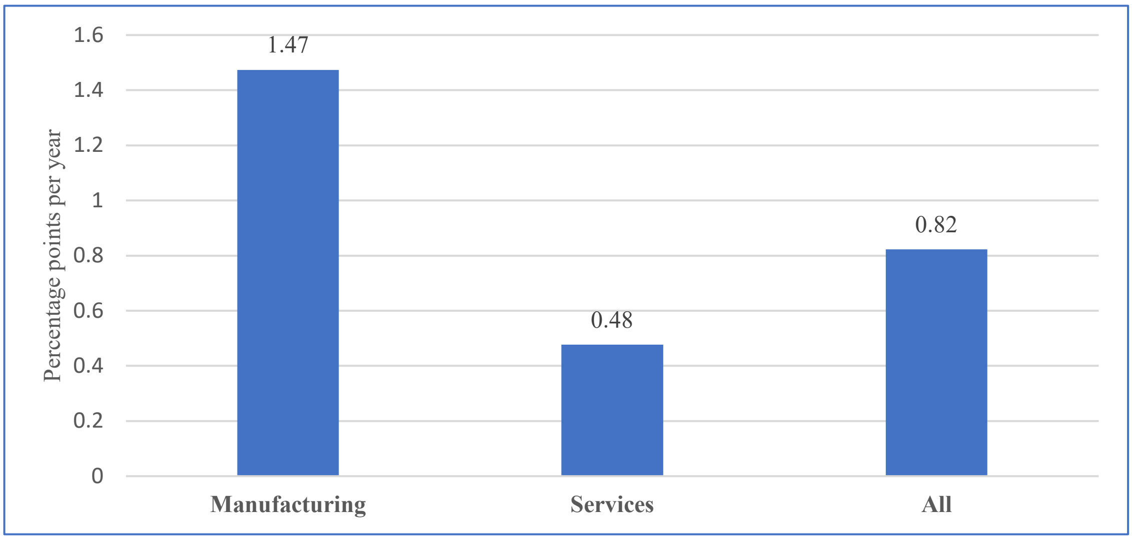
While it became evident that aggregate market power in Romania has been rising, it is important to analyze its consequences for economic growth. An indirect way to measure this is to estimate the productivity dividends that would come from markup reduction. The association between markup and productivity can be positive or negative, depending on the nature of competition in the specific markets/sectors. As shown by Autor et al. (2017) and Van Reenen (2018), there are markets—such as high-tech sectors or knowledge-intensive ones—where the nature of competition tends to emphasize the importance of network effects, economies of scale and scope, and intangible assets, so the most productive and dynamic firms exert higher markups and obtain larger market shares. On the other hand, in certain markets, where recouping fixed costs (such as R&D) because of higher-risk investments is not that relevant, high-markup firms are not necessarily more productive and efficient. Another way to look at this contrast is through the inverted-U relationship of innovation and competition to an increase in productivity, as explored by Aghion et al. (2005). According to this view, stronger competition (proxied here by smaller markups) encourages neck-and-neck firms to innovate—the "escape competition" effect—and therefore to increase productivity growth. At the same time, this view discourages laggard firms from innovating (the Schumpeterian effect), therefore reducing productivity growth. The combination of the two effects—escaping competition and discouraging innovation—explains the inverted-U relationship of competition and innovation with productivity growth.

To assess the correlation between productivity growth and markups in Romania, the analysis uses firm-level estimations of TFPR and markups obtained so far. Thus it estimates the specification presented in Aghion, Braun, and Fedderke (2008) as follows:

$$\Delta lnTFPR_{cjit} = \phi_0 + \phi_1 \mu_{cjit} + \eta_t + \rho_j + \gamma_c + \upsilon_{cjit} \text{ ,} \tag{13}$$

where the left-hand-side variable represents TFPR growth of firm i in NACE 4-digit sector j in year t, μ_{ijt-1} is the lagged value of firm i's markup in sector j in year t, η_t, ρ_j, and γ_c are respectively time, NACE 4-digit sector, and county fixed effects. Equation (13) is estimated separately for each 1-digit sector (that is, manufacturing, services, and mining) and for the whole economy, while the equation parameters are estimated by OLS, always using heteroscedasticity-robust standard errors.

Figure 14. Productivity (TFPR) growth dividends from a 10 percent reduction of average markup, by sector



Source: World Bank staff calculations based on SBS data set.
Note: Results from year, county, and 4-digit sector fixed effects. Coefficient for mining was not statistically significant.

Results shows that on average, reducing markups would have a positive impact on aggregate productivity expansion. Results displayed in table A1.8 in annex 1 suggest that lower (past) markups are associated with higher (current) productivity growth: all coefficients for lagged markups are negative and statistically significant at conventional values for all sectors except mining. Overall, this negative correlation between past markup level and productivity growth is an indication of a positive association between competition and productivity growth, which would be driven by the escape competition effect described by Aghion et al. (2008).[34]

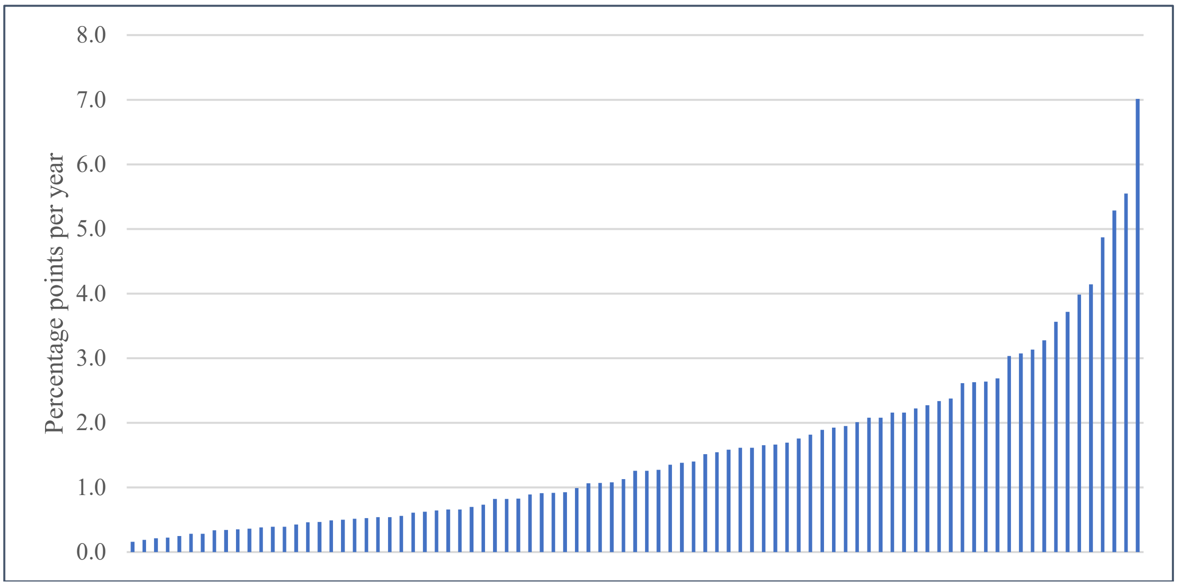
The magnitude of the economic effect of markup reduction on productivity growth is sizable. Figure 14 shows that a 10 percent decrease in the average markup of 6.1 percent for the overall economy in the 2008–17 period would imply an increase in productivity (TFPR) growth of 0.82 percentage point per year. The economic effect for the manufacturing sector would be substantially higher: reducing the average markup of 4.03 percent for manufacturing in the same period would imply an increase in TFPR growth of 1.47 percentage points per year.

Further, productivity dividends stemming from markup reduction vary substantially across NACE 4-digit sectors. The same specification expressed in equation (9) is estimated for each NACE 4-digit sector separately, controlling for year and county fixed effects. The TFPR growth dividends from markup reduction are computed for each NACE 4-digit sector drawing from the estimated coefficients (see table A18 in annex 1). Results vary substantially

[34] An extended specification—where the squared value of lagged markup is included as an additional dependent variable—was also estimated. The estimated coefficient of the squared term was not statistically significant (see results in table A1.7 in annex 1).

across sectors: among those 4-digit sectors where the estimated coefficients are statistically significant, the productivity growth dividends of a 10 percent decrease in markup vary from 7.01 percentage points to 0.16 percentage points, respectively, for NACE sector 1041–Manufacture of oil and fats and sector 4649–Wholesale of other household goods (figure 15).[35] Productivity dividends from a potential markup reduction are also positive in sectors where the top decile firms in the markup distribution are overly represented; for instance, in sector 4711–Retail sale in non-specialized stores with food, beverages or tobacco predominating, a 10 percent decrease of average markup would be associated with an increase in TFPR growth of 0.22 percentage points per year. For sector 4690–Non-specialized wholesale trade and sector 4673–Wholesale of wood, construction materials and sanitary equipment, the productivity dividends would be 0.18 and 0.21 percentage points, respectively.

Figure 15. Productivity (TFPR) growth dividends from a 10 percent reduction of average markup: Results by NACE 4-digit sector



Source: World Bank staff calculations based on SBS data set.

[35] There are, however, some sectors where markup reduction brings detrimental impacts to productivity expansion. See complete set of results in table A1.8in annex 1, for instance, in NACE sector 8010–Private security activities and sector 2432–Precious metals production, where a reduction of average markup in the 2008–17 period would imply a decrease of TFPR growth of 0.30 percentage points and 6.63 percentage points, respectively**.** Following Aghion, Braun, and Fedderke (2008), the Schumpeterian effect of product market competition would be the underlying driver behind this result; in these sectors, competition reduces innovation incentives and therefore productivity growth by reducing the rents from innovations of firms below the technological frontier.

5. Conclusions

A stylized fact emerging in the recent empirical literature is the increase in average levels of market power across countries, in both developed and emerging economies. This paper aims to bring new evidence about the evolution of corporate market power in Romania and the implications for competition dynamics. It uses markups as a proxy for market power and explores firm-level heterogeneity to identify the underlying drivers of aggregate trends. The paper applies the production approach—following De Loecker and Warzynski (2012); De Loecker and Eeckhout (2018); and De Loecker, Eeckhout, and Unger (2020)—to estimate markup at the firm-year level for Romania. The Romanian Structural Business Survey data set is used to apply this methodology.

Results show that the aggregate markup in Romania increased by around 15 percent between 2008 and 2017. However, this aggregate performance masks a lot of heterogeneity, the first being heterogeneity of markups across the main sectors. While in manufacturing, (sales-weighted) average markups experienced a declining pattern of −5.7 percent during 2008–17, there was an opposite, and much more rapid, trend in services, with an aggregate change of 42.2 percent.

Second, at the firm level, results suggest that a key driving force behind this aggregate trend was the ability of the top decile of firms in the markup distribution to increase their markups. This increase has been faster than for the rest of the firms. Firms in the 90th percentile of the markup distribution increased their (sales-weighted) average markup by 28.5 percent between 2008 and 2017, while the rest of firms (that is, those below the top decile firms) experienced a completely opposite trend: their weighted markup contracted by 8.3 percent over the same period.

This sample of top decile firms does not seem to follow the typical superstar firms' profile, which suggests that the increase in markups in Romania might be associated with an environment that is less conducive to competition. The top decile firms in the markup distribution are 46.8 percent smaller, 91.0 percent less productive, and 33 percent less likely to invest in intangible assets than the rest of the firms in the markup distribution, and they are overrepresented in less knowledge-intensive service sectors. Therefore, they do not seem to follow the typical superstar firms' profile (typically larger, more productive, and more likely to invest in intangible assets). This suggests that the increase in markups in Romania might be more due to relatively weak competition rather than to changes in the nature of competition, where superstar firms (usually more efficient and innovative) are rewarded with greater market share. In fact, a decomposition exercise shows that the increase in aggregate markups has been driven mostly by incumbents rather than by new entrants and exiting firms. These results could be interpreted as a sign of consolidation of market power among existing firms. Several policy-related factors could explain this result; among them, government interventions and regulations that restrict competition by reinforcing dominance or limiting entry, facilitating collusive outcomes, or increasing the cost to compete in markets, and by discriminating and protecting vested interests. In this regard, illustrative evidence provided by Pop and Ore Monago (2020) shows that despite reforms, regulations that restrict entry and rivalry are still present in the retail trade sector, which concentrates a substantial proportion of high-markup firms in the Romanian economy.

Results also show that certain firm characteristics matter in explaining differences in markup performance: size, age, R&D profile, export propensity, location, and, notably, ownership. State-controlled companies tend to demonstrate the highest markup premiums when compared with domestic privately owned companies: 28.9 percent higher for minority state-owned companies and 20 percent higher for fully state-owned companies. Old companies (older than 15 years) display 5.4 percent higher markups, on average, than young ones, no matter the product market (at NACE 4-digit level) where they operate. The markup premium for large companies (with more than 250 full-time employees) is 12.2 percent higher than that of small firms in the overall economy. Exporting firms—those whose direct exports represent more than 10 percent of total revenue—earn 11.9 percent higher markups than non-exporting firms that operate in the same sector. At the same time, results show that the markup premium for R&D performers (compared with non-R&D performers) is 27.3 percent for the whole economy, and that firms operating in the same product market charge different markups depending on the county where they operate. Overall, while all these features matter to explain markup performance, a variance decomposition analysis suggests that ownership is the most relevant characteristic to explain total variance of markup performance across firms in Romania.

In this context, given that ownership assumes a prominent role to explain markup performance, it is important to ensure competitively neutral policies across markets where private and public enterprises compete. The prominent role of ownership in explaining total variance of markup performance across firms, combined with the evidence that state-controlled companies tend to exert the highest markup premiums in the overall economy, highlights the importance of ensuring competitive neutrality in Romania so that private and public enterprises compete on a fair basis. Analysis presented in Pop and Ore Monago (2020) shows that state-owned enterprises (SOEs) in Romania compete on uneven terms with the private sector because of gaps in terms of both the current regulatory framework as well as its implementation. As for the regulatory framework itself, lack of competitive neutrality emerges from restrictive SOE governance rules and the exemption of newly setup SOEs from the corporate governance law, lack of rules mandating the separation of commercial and noncommercial functions despite legal separation (for example, in the railway and energy sectors), and the lack of specific provisions that require SOE investments to show positive rates of returns. With regard to implementation of the regulatory framework, competitive neutrality gaps stem from (a) the protracted application of corporate governance rules, (b) fragmentation of SOE oversight across institutions with frequent overlaps, (c) inconsistent reporting of SOE performance that prevents full monitoring and comparability with the private sector performance in comparable situations, (d) little clarity in terms of compensation for public service obligations, and (e) lack of transparency in state aid allocation.

Finally, the analysis shows that productivity dividends arise from increased competition in Romania. As such, lowering markups can boost productivity growth. A 10 percent decrease in the average markup for the overall economy during 2008–17 would imply an increase in productivity (TFPR) growth of 0.82 percentage point per year. The effect for the manufacturing sector is higher (1.47 percentage points per year), but lower for services (0.48 percentage point per year). The "escape competition" effect described by Aghion, Braun, and Fedderke (2008)—through which fiercer competition induces firms to innovate to escape competition with the fringe, therefore increasing productivity growth—would be the underlying driver behind these average results for the manufacturing industry. Results vary substantially across sectors: among those 4-digit sectors where the estimated coefficients are statistically significant, the productivity growth dividend of a 10 percent decrease in markup varies from 7.01 percentage points (sector 1041–Manufacture of oil and fats) to 0.16 percentage point (sector 4649–Wholesale of other household goods).

In this context, boosting competition becomes a key part of the engine to drive productivity growth and help consolidate Romania's convergence to a high-income level. Implementing pro-competition policies is instrumental. Besides removing anticompetitive regulations and promoting competitive neutrality, policy makers should ensure that state aid is allocated in a non-distortive way and enable more effective competition law and antitrust enforcement.

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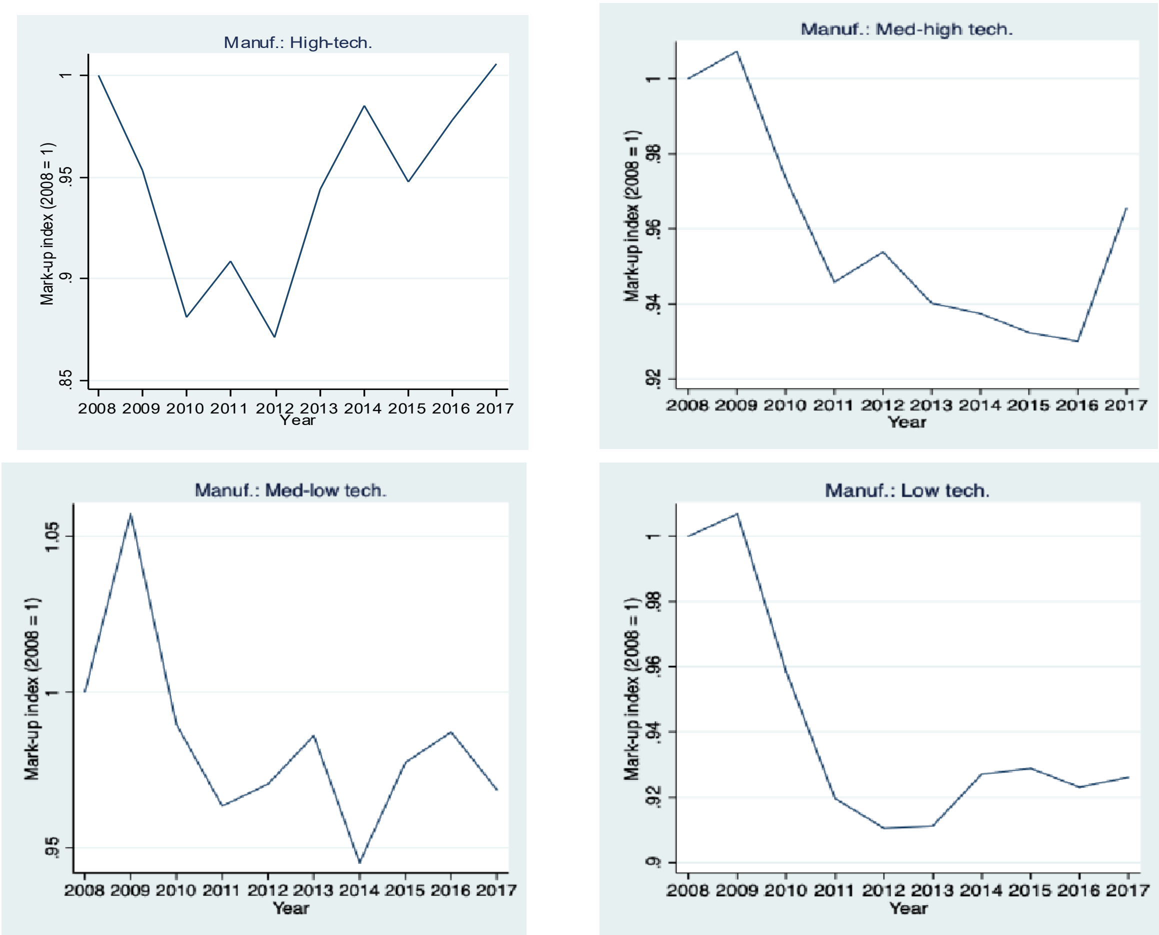
ANNEX 1. ADDITIONAL FIGURES AND TABLES

Figure A1.1 Evolution of (sales-weighted) average markup in manufacturing sector, by technology intensity, 2008–17



Source: World Bank staff calculations based on SBS data set.

Table A1.1 Manufacturing industry groups by technology intensity, Eurostat classification

Manufacturing Industries	NACE Rev. 2 codes – 2-digit level	
High-technology	21	Manufacture of basic pharmaceutical products and pharmaceutical preparations;
	26	Manufacture of computer, electronic and optical products
Medium-high-technology	20	Manufacture of chemicals and chemical products;
	27 to 30	Manufacture of electrical equipment; Manufacture of machinery and equipment n.e.c. ; Manufacture of motor vehicles, trailers and semi-trailers; Manufacture of other transport equipment
Medium-low-technology	19	Manufacture of coke and refined petroleum products;
	22 to 25	Manufacture of rubber and plastic products; Manufacture of other non-metallic mineral products; Manufacture of basic metals; Manufacture of fabricated metals products, excepts machinery and equipment;
	33	Repair and installation of machinery and equipment
Low technology	10 to 18	Manufacture of food products, beverages, tobacco products, textile, wearing apparel, leather and related products, wood and of products of wood, paper and paper products, printing and reproduction of recorded media;
	31 to 32	Manufacture of furniture; Other manufacturing

Source: Eurostat Indicators on High-Tech Industry and Knowledge–Intensive Services, annex 3. https://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an3.pdf.

Figure A1.2 Evolution of (sales-weighted) average markup in services sector, by knowledge intensity

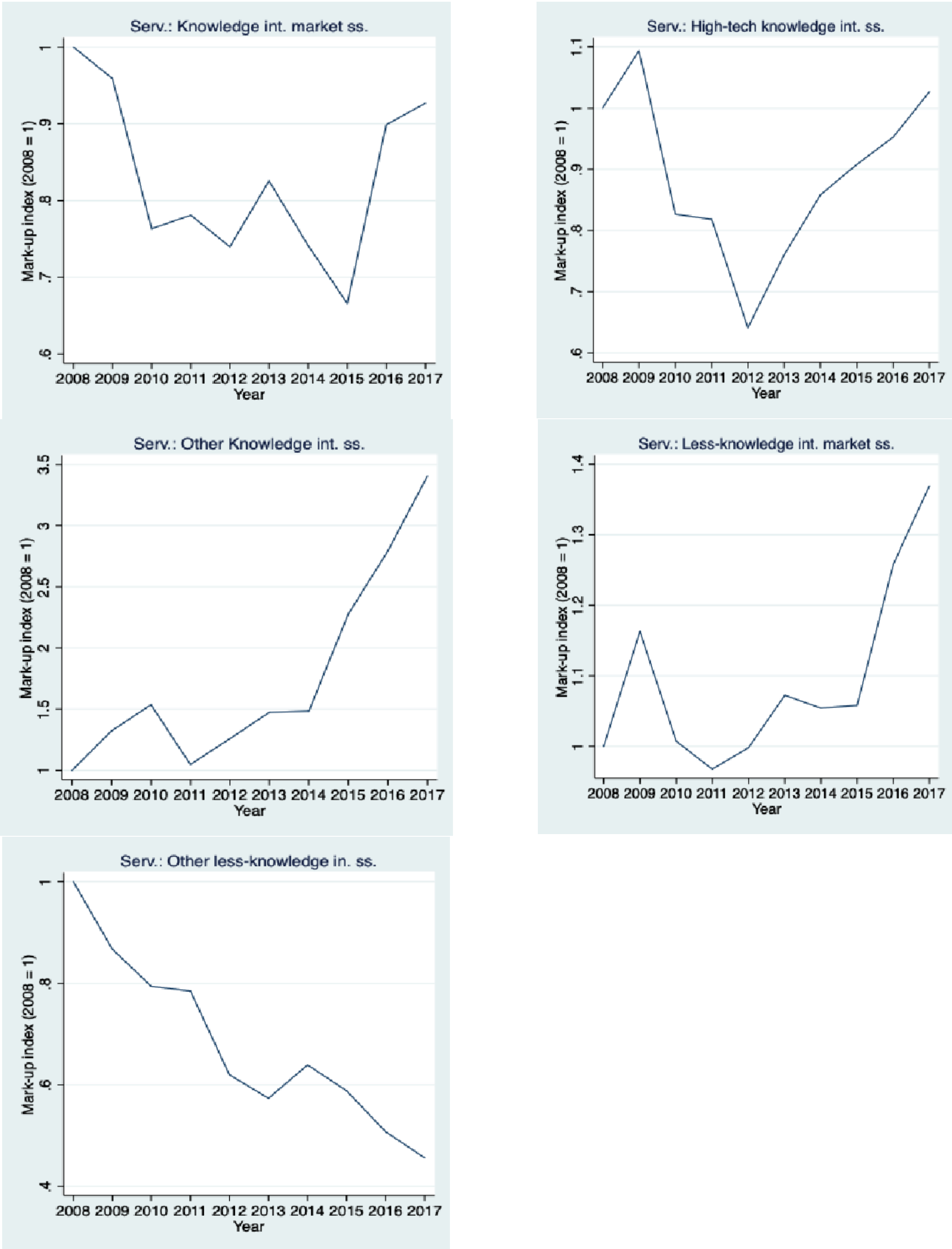


Table A1.2 Services groups by knowledge intensity, Eurostat classification

Knowledge based services	NACE Rev. 2 codes – 2-digit level	
Knowledge-intensive services (KIS)	50 to 51	Water transport; Air transport;
	58 to 63	Publishing activities; Motion picture, video and television programme production, sound recording and music publish activities; Programming and broadcasting activities; Telecommunications; computer programming, consultancy and related activities; Information service activities (section J);
	64 to 66	Financial and insurance activities (section K);
	69 to 75	Legal and accounting activities; Activities of head offices, management consultancy activities; Architectural and engineering activities, technical testing and analysis; Scientific research and development; Advertising and market research; Other professional, scientific and technical activities; Veterinary activities (section M);
	78	Employment activities;
	80	Security and investigation activities;
	84 to 93	Public administration and defence, compulsory social security (section O); Education (section P), Human health and social work activities (section Q); Arts, entertainment and recreation (section R).
Knowledge-intensive market services (excluding high-tech and financial services)	50 to 51	Water transport; Air transport;
	69 to 71	Legal and accounting activities; Activities of head offices, management consultancy activities; Architectural and engineering activities, technical testing and analysis;
	73 to 74	Advertising and market research; Other professional, scientific and technical activities;
	78	Employment activities;
	80	Security and investigation activities;
High-tech knowledge-intensive services	59 to 63	Motion picture, video and television programme production, sound recording and music publish activities; Programming and broadcasting activities; Telecommunications; computer programming, consultancy and related activities; Information service activities;
	72	Scientific research and development;
Knowledge-intensive financial services	64 to 66	Financial and insurance activities (section K).
Other knowledge-intensive services	58	Publishing activities;
	75	Veterinary activities;
	84 to 93	Public administration and defence, compulsory social security (section O); Education (section P), Human health and social work activities (section Q); Arts, entertainment and recreation (section R).

Knowledge based services	NACE Rev. 2 codes – 2-digit level	
Less knowledge-intensive services (LKIS)	45 to 47	Wholesale and retail trade; Repair of motor vehicles and motorcycles (section G);
	49	Land transport and transport via pipelines;
	52 to 53	Warehousing and support activities for transportation; Postal and courier activities;
	55 to 56	Accommodation and food service activities (section I);
	68	Real estate activities (section L);
	77	Rental and leasing activities;
	79	Travel agency, tour operator reservation service and related activities;
	81	Services to buildings and landscape activities;
	82	Office administrative, office support and other business support activities;
	94 to 96	Activities of membership organisation; Repair of computers and personal and household goods; Other personal service activities (section S);
	97 to 99	Activities of households as employers of domestic personnel; Undifferentiated goods- and services-producing activities of private households for own use (section T); Activities of extraterritorial organisations and bodies (section U).
Less knowledge-intensive market services	45 t6 47	Wholesale and retail trade; Repair of motor vehicles and motorcycles (section G);
	49	Land transport and transport via pipelines;
	52	Warehousing and support activities for transportation;
	55 to 56	Accommodation and food service activities (section I);
	68	Real estate activities (section L);
	77	Rental and leasing activities;
	79	Travel agency, tour operator reservation service and related activities;
	81	Services to buildings and landscape activities;
	82	Office administrative, office support and other business support activities;
	95	Repair of computers and personal and household goods;
Other less knowledge-intensive services	53	Postal and courier activities;
	94	Activities of membership organisation;
	96	Other personal service activities;
	97 to 99	Activities of households as employers of domestic personnel; Undifferentiated goods- and services-producing activities of private households for own use (section T); Activities of extraterritorial organisations and bodies (section U).

Source: Eurostat Indicators on High-Tech Industry and Knowledge–Intensive Services, annex 3. https://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an3.pdf.

Table A1.3 Original ownership classification from SBS

SBS Code	Description
10	**Fully state-owned**
Majority state-owned (state/public capital > 50% of equity)	
21	State + Romanian private
22	State + foreign
23	State + Romanian private + foreign
Majority privately owned (private capital ≥ 50% of equity)	
26	State + Romanian private
27	State + foreign
28	State + Romanian private + foreign
Fully privately owned	
31	Romanian private
32	Romanian private + foreign
40	**Cooperative**
50	**Craft organizations**
60	**Fully foreign-owned**
70	**Public of national and local interest**

Source: World Bank staff calculations based on SBS data set.

Table A1.4 Ownership classification adopted in the analysis

SBS codes (combined)	Description
10, 21, 22, 23	State owned (fully + majority state-owned)
26, 27, 28	Private-public (majority private)
31	Fully private (domestic)
32	Fully private (domestic + foreign)
60	Fully private (fully foreign)
70	Public of national and local interest
40, 50	Other

Source: World Bank staff calculations based on SBS data set.

Table A1.5 Conditional correlations between firm characteristics and markup performance, regression results

Variable	Manufacturing	Services	Mining	All
Capital stock (ln)	−0.150***	−0.039***	−0.067***	−0.066***
Export dummy	0.120***	0.258***	0.416***	0.119***
R&D dummy	0.160***	0.340***	0.460***	0.273***
Mature	0.022**	−0.016**	0.158***	−0.005
Old	0.079***	0.048***	0.228***	0.054***
Majority state-owned	0.527***	0.139***	0.772***	0.200***
State-private ownership	0.352***	0.275***	0.111	0.289***
Romanian private + foreign	0.161***	0.279***	0.096	0.229***
Fully foreign-owned	0.105***	0.263***	0	0.201***
Public of national and local interest	0.209	0.149*	(omitted)	0.214***
Other	0.884***	0.555***	(omitted)	0.758***
Medium	0.230***	−0.083***	0.011	0.009*
Large	0.327***	0.169***	−0.015	0.122***
1 Alba	0.106***	−0.087***	−0.151	−0.042**
2 Arad	0.038*	−0.090***	−0.148	−0.077***
3 Arges	−0.005	−0.053***	−0.195	−0.060***

Variable	Manufacturing	Services	Mining	All
4 Bacau	0.092***	−0.090***	−0.194*	−0.055***
5 Bihor	0.036**	−0.115***	−0.256**	−0.088***
6 Bistrita-Nasaud	−0.064***	−0.156***	−0.069	−0.144***
7 Botosani	0.046*	−0.089***	−0.438***	−0.076***
8 Brasov	0.041***	−0.047***	0.049	−0.040***
9 Braila	0.133***	−0.055**	−0.265*	−0.025
10 Buzau	0.017	−0.123***	−0.025	−0.100***
11 Caras-Severin	0.035	−0.187***	−0.005	−0.139***
12 Cluj	−0.004	−0.094***	−0.119	−0.088***
13 Constanta	0.057***	−0.105***	0.062	−0.088***
14 Covasna	0.038*	−0.056*	−0.151	−0.052***
15 Dambovita	0.005	−0.183***	−0.154	−0.144***
16 Dolj	0.195***	0.060***	−0.042	0.079***
17 Galati	0.106***	−0.007	−0.276***	0.004
18 Gorj	0.084***	0.028	−0.116	0.026
19 Harghita	0.101***	−0.102***	−0.007	−0.045***
20 Hunedoara	0.167***	−0.031*	−0.057	0.011
21 Ialomita	0.138***	−0.049*	−0.265***	−0.027
22 Iasi	−0.014	−0.038**	−0.384**	−0.058***
23 Ilfov	0.011	0.009	0.314	0.010
24 Maramures	0.094***	−0.020	−0.042	0
25 Mehedinti	0.113***	−0.136***	−0.720***	−0.096***
26 Mures	0.048***	−0.063***	−0.093	−0.048***
27 Neamt	0.001	−0.108***	−0.428***	−0.102***
28 Olt	0.073***	−0.005	−0.397***	−0.011
29 Prahova	0.018	−0.034**	−0.028	−0.043***
30 Satu-Mare	0.033*	−0.024	−0.056	−0.036**
31 Salaj	0.075***	−0.045*	−0.448*	−0.031
32 Sibiu	0.044**	−0.038**	−0.154	−0.041***
33 Suceava	0.044**	−0.087***	−0.111	−0.074***
34 Teleorman	0.103***	−0.099***	−0.299	−0.062**
35 Timis	0.030*	−0.020	−0.341***	−0.037***
36 Tulcea	0.142***	−0.149***	0.096	−0.078***
37 Vaslui	0.091***	−0.017	−0.105	−0.007
38 Valcea	0.078***	−0.008	−0.122	−0.002
39 Vrancea	−0.061***	−0.163***	−0.608***	−0.154***
51 Calarasi	0.080**	−0.122***	0.672	−0.075***
52 Giurgiu	0.052	−0.064*	−0.334***	−0.066**
_cons	2.147***	1.150***	2.291***	2.246***
NACE 4-digit fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
R^2	0.345	0.235	0.254	0.279

Source: World Bank staff calculations based on SBS data set.
Note: Dependent variable = ln(markup).
***denotes significance level at 1 percent; **at 5 percent and * at 10 percent.

Table A1.6 Conditional correlations between firm characteristics (including productivity) and markup performance, regression results

Variable	Manufacturing	Services	Mining	All
Capital stock (ln)	−0.149***	−0.038***	−0.065***	−0.066***
Export dummy	0.116***	0.257***	0.400***	0.118***
R&D dummy	0.182***	0.366***	0.449***	0.295***
Mature	0.021**	−0.014*	0.164***	−0.003
Old	0.079***	0.052***	0.228***	0.057***
Majority state-owned	0.529***	0.147***	0.758***	0.209***
State-private ownership	0.351***	0.274***	0.118	0.288***
Romanian private + foreign	0.156***	0.275***	0.090	0.225***
Fully foreign-owned	0.096***	0.254***	−0.011	0.192***
Public of national and local interest	0.179	0.165**	(omitted)	0.233***
Other	0.879***	0.561***	(omitted)	0.759***
Medium	0.232***	−0.083***	0.002	0.010*
Large	0.327***	0.170***	−0.016	0.122***
Productivity (TFPR)	0.051***	0.020***	0.041	0.024***
1 Alba	0.114***	−0.081***	−0.156	−0.035**
2 Arad	0.045**	−0.085***	−0.135	−0.071***
3 Arges	0.001	−0.049***	−0.196	−0.056***
4 Bacau	0.098***	−0.084***	−0.188*	−0.049***
5 Bihor	0.042**	−0.111***	−0.268**	−0.083***
6 Bistrita-Nasaud	−0.057***	−0.150***	−0.055	−0.137***
7 Botosani	0.053**	−0.082***	−0.443***	−0.069***
8 Brasov	0.045***	−0.042***	0.033	−0.035***
9 Braila	0.139***	−0.048*	−0.243	−0.018
10 Buzau	0.022	−0.118***	−0.002	−0.094***
11 Caras-Severin	0.042	−0.178***	−0.001	−0.131***
12 Cluj	−0.001	−0.089***	−0.120	−0.083***
13 Constanta	0.067***	−0.101***	0.056	−0.084***
14 Covasna	0.045**	−0.050*	−0.166	−0.046**
15 Dambovita	0.010	−0.180***	−0.162	−0.140***
16 Dolj	0.202***	0.068***	−0.054	0.087***
17 Galati	0.114***	−0.001	−0.289***	0.010
18 Gorj	0.091***	0.037	−0.118	0.035*
19 Harghita	0.108***	−0.096***	−0.005	−0.039***
20 Hunedoara	0.173***	−0.025	−0.055	0.018
21 Ialomita	0.144***	−0.045	−0.256***	−0.023
22 Iasi	−0.005	−0.034**	−0.394**	−0.053***
23 Ilfov	0.013	0.012	0.296	0.013
24 Maramures	0.101***	−0.013	−0.038	0.007
25 Mehedinti	0.128***	−0.132***	−0.729***	−0.090***
26 Mures	0.053***	−0.057***	−0.105	−0.042***
27 Neamt	0.010	−0.101***	−0.434***	−0.094***

Variable	Manufacturing	Services	Mining	All
28 Olt	0.082***	0.002	−0.402***	−0.004
29 Prahova	0.023*	−0.029*	−0.032	−0.039***
30 Satu-Mare	0.038**	−0.018	−0.047	−0.030**
31 Salaj	0.081***	−0.039	−0.433*	−0.025
32 Sibiu	0.044**	−0.034*	−0.147	−0.038***
33 Suceava	0.051***	−0.081***	−0.105	−0.068***
34 Teleorman	0.117***	−0.092***	−0.296	−0.053**
35 Timis	0.033**	−0.014	−0.340***	−0.032***
36 Tulcea	0.147***	−0.142***	0.078	−0.072***
37 Vaslui	0.101***	−0.011	−0.104	0
38 Valcea	0.087***	−0.002	−0.120	0.004
39 Vrancea	−0.053**	−0.158***	−0.602***	−0.148***
51 Calarasi	0.086***	−0.118***	0.673	−0.071***
52 Giurgiu	0.059*	−0.060*	−0.334***	−0.061**
_cons	1.632***	0.993***	1.934***	2.036***
NACE 4-digit fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
R^2	0.347	0.235	0.255	0.280

Source: World Bank staff calculations based on SBS data set.
Note: Dependent variable = ln(markup).
***denotes significance level at 1 percent; **at 5 percent and * at 10 percent.

Table A1.7 Productivity growth and markup performance, regression results

	All		Manufacturing		Services		Mining	
Lag markup	−0.025***	−0.028***	−0.026***	−0.027*	−0.025***	−0.027***	−0.012	−0.024
Lag markup squared		0.001		0.000		0.001		0.003
NACE 4-digit sector fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	245,525	245,525	76,694	76,694	167,120	167,120	1,711	1,711

Source: World Bank staff calculations based on SBS data set.
Note: Dependent variable = TFPR growth.
***denotes significance level at 1 percent; **at 5 percent and * at 10 percent.

Table A1.8 Productivity (TFPR) growth dividends from a 10% reduction of average markup, results by NACE 4-digit sector

NACE 4-digit sector	Gain in TFPR growth per year (percentage points)
1041–Manufacture of oils and fats	7.015
4331–Plastering	5.547
2060–Manufacture of man-made fibers	5.286
2824–Manufacture of power-driven hand tools	4.869
1072–Manufacture of rusks and biscuits; manufacture of preserved pastry goods and cakes	4.145
1104–Manufacture of other non-distilled fermented beverages	3.984
1723–Manufacture of paper stationery	3.716
2812–Manufacture of fluid power equipment	3.566
2452–Casting of steel	3.278
1101–Distilling, rectifying and blending of spirits	3.134
1420–Raising of other cattle and buffaloes	3.072
2011–Manufacture of industrial gases	3.033
2593–Manufacture of wire products, chain and springs	2.689
2829–Manufacture of other general-purpose machinery n.e.c.	2.641
4910–Passenger rail transport, interurban	2.629
2451–Casting of iron	2.615
3821–Treatment and disposal of non-hazardous waste	2.375
2059–Manufacture of other chemical products n.e.c.	2.336
2920–Manufacture of bodies (coachwork) for motor vehicles; manufacture of trailers and semi-trailers	2.270
1051–Operation of dairies and cheese making	2.224
3313–Repair of electronic and optical equipment	2.160
1081–Manufacture of sugar	2.158
1073–Manufacture of macaroni, noodles, couscous and similar farinaceous products	2.081
4213–Construction of bridges and tunnels	2.077
2223–Manufacture of builders’ ware of plastic	2.011
2550–Forging, pressing, stamping and roll-forming of metal; powder metallurgy	1.949
2313–Manufacture of hollow glass	1.926
2825–Manufacture of non-domestic cooling and ventilation equipment	1.889
2020–Manufacture of pesticides and other agrochemical products	1.818
2571–Manufacture of cutlery	1.758
5914–Motion picture projection activities	1.691
5920–Sound recording and music publishing activities	1.665
3514–Trade of electricity	1.653
1310–Preparation and spinning of textile fibers	1.616
4920–Freight rail transport	1.613
4339–Other building completion and finishing	1.586
2620–Manufacture of computers and peripheral equipment	1.543
4311–Demolition	1.515
3832–Recovery of sorted materials	1.404
3523–Trade of gas through mains	1.382
2410–Manufacture of basic iron and steel and of ferro-alloys	1.353
2399–Manufacture of other non-metallic mineral products n.e.c.	1.272
2017–Manufacture of synthetic rubber in primary forms	1.258
7711–Rental and leasing of cars and light motor vehicles	1.256
4212–Construction of railways and underground railways	1.128
2453–Casting of light metals	1.080
7410–Specialized design activities	1.068
5630–Beverage serving activities	1.065
4211–Construction of roads and motorways	0.989
4677–Wholesale of waste and scrap	0.926
4676–Wholesale of other intermediate products	0.917
4120–Construction of residential and non-residential buildings	0.912
4623–Wholesale of live animals	0.890
6820–Rental and operating of own or leased real estate	0.826
4110–Development of building projects	0.824

NACE 4-digit sector	Gain in TFPR growth per year (percentage points)
4613–Agents involved in the sale of timber and building materials	0.823
4322–Plumbing, heat and air-conditioning installation	0.731
5629–Other food service activities	0.699
4791–Retail sale via mail order houses or via internet	0.659
4941–Freight transport by road	0.659
4618–Agents specialized in the sale of other particular products	0.646
7219–Other research and experimental development on natural sciences and engineering	0.623
4617–Agents involved in the sale of food, beverages and tobacco	0.609
5510–Hotels and similar accommodation	0.560
4615–Agents involved in the sale of furniture, household goods, hardware and ironmongery	0.541
4633–Wholesale of dairy products, eggs and edible oils and fats	0.540
4778–Other retail sale of new goods in specialized stores	0.527
4621–Wholesale of grain, unmanufactured tobacco, seeds and animal feeds	0.517
4662–Wholesale of machine tools	0.501
6110–Wired telecommunications activities	0.491
4634–Wholesale of beverages	0.468
5610–Restaurants and mobile food service activities	0.463
4631–Wholesale of fruit and vegetables	0.426
4532–Retail trade of motor vehicle parts and accessories	0.394
1411–Manufacture of leather clothes	0.390
4511–Sale of cars and light motor vehicles	0.382
4637–Wholesale of coffee, tea, cocoa and spices	0.361
4645–Wholesale of perfume and cosmetics	0.354
1419–Manufacture of other wearing apparel and accessories	0.344
4643–Wholesale of electrical household appliances	0.335
4639–Non-specialized wholesale of food, beverages and tobacco	0.285
4619–Agents involved in the sale of a variety of goods	0.281
4675–Wholesale of chemical products	0.249
4711–Retail sale in non-specialized stores with food, beverages or tobacco predominating	0.223
4673–Wholesale of wood, construction materials and sanitary equipment	0.214
4690–Non-specialized wholesale trade	0.188
4649–Wholesale of other household goods	0.158
8010–Private security activities	−0.300
8220–Activities of call centres	−0.323
2572–Manufacture of locks and hinges	−0.503
7120–Technical testing and analysis	−0.511
3315–Repair and maintenance of ships and boats	−0.512
3600–Water collection, treatment and supply	−0.547
4754–Retail sale of electrical household appliances in specialized stores	−0.627
2341–Manufacture of ceramic household and ornamental articles	−0.646
7111–Architectural activities	−0.649
6120–Wireless telecommunications activities	−0.746
7312–Media representation	−1.023
4334–Painting and glazing	−1.200
5020–Sea and coastal freight water transport	−1.276
1052–Manufacture of ice cream	−1.367
5911–Motion picture, video and television programme production activities	−1.439
2592–Manufacture of light metal packaging	−1.619
2752–Manufacture of non-electric domestic appliances	−1.729
2521–Manufacture of central heating radiators and boilers	−1.843
4932–Taxi operation	−2.568
2013–Manufacture of other inorganic basic chemicals	−3.524
1711–Manufacture of pulp	−3.631
4942–Removal services	−4.214
1092–Manufacture of prepared pet foods	−4.262
3040–Manufacture of military fighting vehicles	−5.508
2432–Cold rolling of narrow strip	−6.629

Source: World Bank staff calculations based on SBS data set.
Note: The table displays only sectors for which estimated coefficients are statistically significant.

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