ANNEX I. FURTHER DETAILS ON MARKET POWER, BUSINESS DYNAMISM, AND M&AS[1]

A. Data Sources

The empirical analysis in this note is based on two datasets, each of them merging data on firms' financial information with data on M&A deals.

First, the main analysis on market power uses Worldscope data, obtained through Datastream provided by Thomson Reuters. It contains information on financial fundamentals and ratios from over 81,000 publicly listed companies, accounting for over 99% of world market capitalization. For advanced economies, the data date back to the 1980s; for most emerging markets, the data start from the 1990s. These data were used to compute markups, concentration, and profitability measures reported in the main text—after selecting countries with enough observations and some data cleaning, markups were computed for 47,000 firms from 82 countries (see Díez, Leigh, and Tambunlertchai 2018 for details on markup calculation).

Information on M&A deals was obtained from Securities Data Company (SDC) Platinum provided by Thomson Reuters. This dataset has information on deal characteristics (such as value, type, etc.) as well as the characteristics of the companies involved in the deal (firm id, name, sector, origin etc.). The deal-level information from SDC covers around 1 million deals since 1977 with acquirors from 126 countries. The cleaning steps on SDC data involved keeping completed deals; dropping deal types as leveraged buyouts, repurchases, privatizations, self-tenders, exchange offers, recapitalizations and spinoffs; and dropping cases when the acquiror or the target were classified as individual investors, government or mutual funds, or when the acquiror firm was classified as a financial buyer. Using unique firm identifiers, the acquiror's Datastream ID, and the year when the deal became effective, firms involved in M&A deals in SDC were matched to Worldscope.

Second, since the Worldscope-SDC dataset contains information only on publicly listed firms, the analysis is complemented with an additional dataset that includes privately held firms. As explained in the main text, this is particularly important to compute valid measures of business dynamism that affect the whole economy. To this purpose, the analysis uses the Orbis data, a product from Bureau van Dijk that provides financial information on public and private firms. After (significant) cleaning, the resulting dataset covers 12 million firms from 28 countries for the period 2000-2015 (see IMF 2019 and Díez, Fan, and Villegas-Sánchez 2019 for details on the cleaning procedure). Orbis is merged with data on M&A deals from Zephyr, also provided by Bureau van Dijk. The structure of the dataset is similar to SDC—there is information on the characteristics of the deal as well as the firms involved in the deal. The cleaning procedure was

[1] This annex was prepared by Wenjie Chen, Federico J. Díez, Jiayue Fan, and Carolina Villegas-Sánchez.

similar to the one conducted for SDC, keeping only completed deals, and dropping those deals with the entity type classified as assets, mutual funds, government or individual/families for either the acquiror or the target. Both, Orbis and Zephyr, were merged using unique firm identifiers, BvD ID number, and the year when the deal is completed.

Table I.1 present the full list of countries considered in the analysis.

Annex Table I.1. List of Countries in Worldscope Dataset

Argentina	India	Oman
Australia	Indonesia	Peru
Austria*	Ireland*	Philippines
Bahrain, Kingdom of	Israel	Poland*
Bangladesh	Italy*	Portugal*
Belgium*	Jamaica	Qatar
Bosnia and Herzegovina	Japan*	Romania*
Brazil	Jordan	Russia*
Bulgaria*	Kazakhstan	Saudi Arabia
Canada	Kenya	Serbia, Republic of
Chile	Korea, Republic of*	Singapore
China, P.R.: Hong Kong	Kuwait	Slovak Republic*
China, P.R.: Macao	Latvia*	Slovenia*
China, P.R.: Mainland*	Lithuania	South Africa
Colombia	Luxembourg	Spain*
Croatia	Macedonia, FYR	Sri Lanka
Cyprus	Malaysia	Sweden
Czech Republic*	Malta	Switzerland
Denmark*	Mauritius	Thailand
Egypt	Mexico	Tunisia
Estonia*	Montenegro	Turkey*
Finland*	Morocco	Ukraine
France*	Netherlands*	United Arab Emirates
Germany*	New Zealand	United Kingdom*
Ghana	Nigeria	United States*
Greece*	Norway	Venezuela
Hungary*	Pakistan	Vietnam
Iceland		

Asterisk (*) denotes countries in Orbis sample (used for industry-level analysis).

B. Sector-Level Analysis: M&As and Business Dynamism

The main text of the note emphasizes the effects of M&A concentration by leading firms on business dynamism. The underlying analysis uses the merged Orbis-Zephyr database and is conducted at the country-(2-digit NACE) industry level.

The measures of business dynamism considered are (1) the share of total output accounted by young firms (those less than or equal to 5 years-old) in a given country-industry; and (2) the dispersion of firm output growth in the country-industry.[2]

Each measure of business dynamism is regressed on the lagged value of the share of deals by the leading firms, controlling for country, industry, and year fixed effects.[3] Specifically, the estimating equation is the following:

$$BD_{c,s,t} = \beta_0 + \beta_1 Share\ of\ M\&A_{c,s,t-1} + \delta_c + \delta_s + \delta_t + \varepsilon_{c,s,t},$$

where $BD_{c,s,t}$ is the corresponding measure of business dynamism and the country-industry-year and $Share\ of\ M\&A_{c,s,t-1}$ is the lagged share of M&A deals by the top firms in the country-industry, and δ_c, δ_s, δ_t denote country, sector and year fixed effects, respectively.

The results are presented in Annex Tables I.2 and I.3. Both tables have the same structure. Column (1) presents the results from using all deals and defining market leaders as the top 10 percent firms in terms of revenue within a country-industry-year. Column (2) considers only those deals where there is a majority switch in the shares of the target firm (that is, where the acquiring firm becomes, ex post, a majority owner of the target firm). Columns (3) and (4) employ a definition of leading firms as the 20 firms with the largest revenue within a country-industry-year. From both tables it follows that the data indicate that higher shares of M&As by leading firms are associated with lower shares of output accounted by young firms and lower dispersion of firm growth.

[2] The dispersion of firms' output is defined as the difference between the 90 and 10 percentile of the sales weighted firm output growth rate at the country-industry level.

[3] Several measures are considered to define leading firms or market leaders (both terms are used interchangeably)—the top 20, the top 10 percent or the top 5 percent firms in terms of revenue, within a given country-industry-year. All measures yield qualitatively similar results.

Annex Table I.2. M&As and Share of Output by Young Firms

Dependent Variable: Share of Output by Young Firms	(1)	(2)	(3)	(4)
Share of M&As by Top 10% $_{t-1}$	-0.007**			
	(0.003)			
Share of M&As by Top 10% $_{t-1}$ ***(Majority Switches)***		-0.006*		
		(0.003)		
Share of M&As by Top 20 $_{t-1}$			-0.010***	
			(0.003)	
Share of M&As by Top 20 $_{t-1}$ ***(Majority Switches)***				-0.009***
				(0.003)
Number of Observations	11,200	9,887	11,200	9,887
R-squared	0.336	0.337	0.336	0.337

*** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at the country-industry level. All regressions include country, industry, and year fixed effects.

Annex Table I.3. M&As and the Dispersion of Firm Output Growth

Dependent Variable: Dispersion of Firm Output Growth	(1)	(2)	(3)	(4)
Share of M&As by Top 10% $_{t-1}$	-0.042***			
	(0.011)			
Share of M&As by Top 10% $_{t-1}$ ***(Majority Switches)***		-0.036***		
		(0.011)		
Share of M&As by Top 20 $_{t-1}$			-0.044***	
			(0.011)	
Share of M&As by Top 20 $_{t-1}$ ***(Majority Switches)***				-0.046***
				(0.011)
Number of Observations	10,562	9,338	10,562	9,338
R-squared	0.388	0.380	0.388	0.381

*** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at the country-industry level. All regressions include country, industry, and year fixed effects.

C. Firm-Level Analysis: M&As and Firm Performance

Panel regressions were carried out at the firm-level to assess the effect of M&A, especially the M&A deals conducted by market leaders, on firms' growth. The analysis employs merged Worldscope-SDC data for the same 28 countries considered in the industry-level exercise.

The analysis first focuses on the effects that M&As have on the performance of the acquiring firm. In particular, firm growth rate of employment, net sales and R&D expenses (the variables of interest) are regressed on the share of deals by firm i within the country-industry, a *leader* dummy variable, the share of deals interacted with the *leader* dummy variable, and controlling for firm size (proxied by the logarithm of firm total assets), as well as firm, country-industry-year fixed effects. Specifically, the estimating equations take the following form:

$$\begin{aligned} Outcome\ Growth_{i,c,s,t} &= \beta_0 + \beta_1 Share\ of\ M\&As_{i,c,s,t-1} + \beta_2 Share\ of\ M\&As * Leader_{i,c,s,t-1} \\ &+ \beta_3 Leader_{i,c,s,t-1} + \beta_4 Log\_assets_{i,c,s,t-1} + \delta_i + \gamma_{c,s,t} + \varepsilon_{i,c,s,t} \end{aligned}$$

As shown in Annex Table I.4, a higher share of M&A activity is associated with faster employment, sales, and R&D growth by the acquiring firm. However, the negative coefficients on the interaction terms suggest that this faster growth is significantly smaller whenever the acquirer happens to be a market leader.

Annex Table I.4. Own M&As and Firm Growth

	(1) Employment Growth Rate	(2) Net Sales Growth Rate	(3) R&D Growth Rate
Share M&A$_{t-1}$	0.126***	0.202***	0.154***
	(0.009)	(0.013)	(0.056)
(Share M&A * Leader)$_{t-1}$	-0.094***	-0.184***	-0.142*
	(0.014)	(0.015)	(0.076)
Leader$_{t-1}$	0.077***	0.161***	0.089**
	(0.006)	(0.011)	(0.042)
Log Assets$_{t-1}$	-0.129***	-0.217***	-0.131***
	(0.005)	(0.009)	(0.024)
Number of Observations	231,696	263,721	90,088
R-squared	0.255	0.285	0.284

*** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at the firm level. All regressions include firm and country-industry-year fixed effects

A similar analysis is carried out to assess the effects of a firm's competitor's M&As on said firm's growth (instead of its own M&As). Firm *i*'s (closest) competitor is defined as the firm with the smallest distance to *i* in terms of net sales within the corresponding country-industry. The dummy variable for market *leader* is now redefined as whether the closest competitor is one of the market leaders. The estimating equations are analogous to the previous analysis, except that the share M&As and leader dummy variable now refer to the firm's closest competitor. The results shown in Annex Table I.5 indicate that an increase in the share of M&A activity by a firm's competitor is associated with slower growth in employment, net sales and R&D. Moreover, the negative effect on sales growth is even stronger if the firm's competitor is a market leader.

Annex Table I.5. Competitor's M&As and Firm Growth

	(1) Employment Growth Rate	(2) Net Sales Growth Rate	(3) R&D Growth Rate
Share Competitor M&A$_{t-1}$	-0.016**	-0.031***	-0.062*
	(0.007)	(0.007)	(0.033)
(Share Competitor M&A * Leader)$_{t-1}$	-0.003	-0.053***	0.113
	(0.016)	(0.015)	(0.141)
Leader$_{t-1}$	0.053***	0.126***	-0.038
	(0.007)	(0.011)	(0.034)
Log Assets$_{t-1}$	-0.124***	-0.209***	-0.121***
	(0.005)	(0.009)	(0.024)
Firm	Yes	Yes	Yes
Country-Industry(2-digit)-Year	Yes	Yes	Yes
Number of Observations	231,696	263,721	90,088
R-squared	0.253	0.283	0.284

*** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at the firm level. All regressions include firm and country-industry-year fixed effects

D. Firm-Level Analysis: M&As and Firm Performance Using Propensity Score Matching and Difference-in-Differences Estimation

Propensity score matching combined with difference-in-differences estimation methodology was conducted at the firm-level to assess the effect of M&A on firms' profitability and markups. The analysis employs merged Worldscope-SDC data for the same 28 countries considered in the industry-level exercise.

In the first stage, for each calendar year in the sample period, a probit estimation is run. The dependent variable takes on the value of one if a firm is an acquirer and zero otherwise.[4] The independent variables include a firm's sales, its labor productivity, measured as sales divided by employment, and its profitability, with all variables captured from the preceding two years. The probit estimation also includes SIC-2-digit-sector and firm country fixed effects. To create a propensity score for each firm, i.e., a summary index capturing firm characteristics, the predicted probability of becoming an acquirer from the probit estimation is taken.

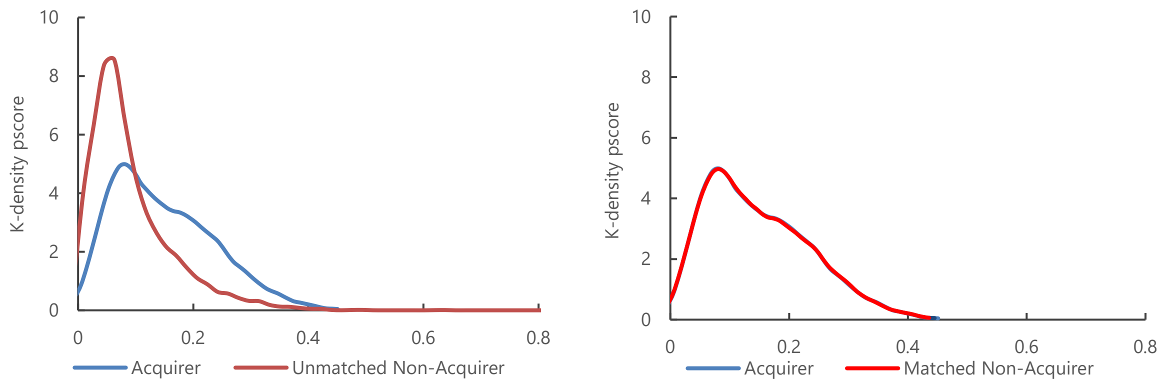
Nearest neighbor matching with replacement is then performed using the propensity score estimated from the probit, and a common support condition is imposed for the matching.[5] Acquiring firms are matched with non-acquiring firms that have the closest propensity score and are in the same 2-digit SIC sector and for the same calendar year. Annex Figure I.1 provides an illustration of how PSM performs.[6] In the left panel graph, the distributions of the acquiring firms and of non-acquiring firms prior to matching are very different. However, once PSM was applied, the distribution of matched non-acquiring firms becomes very similar to that of acquiring firms as displayed in the right panel graph, implying that PSM has performed reasonably well in creating a more similar group of non-acquiring firms based on those observable characteristics included in the probit estimation.

[4] For tractability, only the first acquisition within the sample period of an acquiring firm is considered, while non-acquirers have not conducted any M&As throughout the sample period.

[5] The imposed common support restriction requires that observations are considered off support if the acquirer firm's propensity score is above the maximum value or below the minimum value for the non-acquirer firms.

[6] For illustrative purposes, the example uses 2005. Other years perform similarly.

Annex I.1. Distribution of Propensity Scores by Acquirer, Matched Non-Acquirer and Unmatched Non-Acquirer Firms



Source: SDC Thomson Reuters, Worldscope, and IMF staff calculations.
Notes: The distribution shows the propensity score of acquirer, unmatched, and matched non-acquiring firms, based on nearest neighbor matching with replacement.

After PSM has established this comparison group of matched non-acquiring firms that resembles the group of acquiring firms based on observable characteristics, a difference-in-difference (DID) estimation approach is applied in order to eliminate unobservable time-invariant differences between the acquiring and matched non-acquiring firms. The DID regression equation is the following:

$$Y_{i,c,s,t} = \beta_0 + \beta_1 post_t + \beta_2 post_t * Acq_{i,c,s,t} + \delta_i + \gamma_{c,s,t} + \varepsilon_{i,c,s,t}.$$

The regression is run on the combined sample of acquiring and matched non-acquiring firms for the year of the acquisition and the two subsequent years against the baseline of two years before the acquisition. The outcome variables, captured by *Y*, includes the firm's profitability, measured as operating income divided by total assets, and firm's markups. The regression also includes firm and country-industry-year fixed effects. The coefficient of interest is β_2 which assesses the effect of the acquisition relative to the pre-acquisition period on the performance outcome of interest.

Annex Table I.6 displays the regression results. The coefficient on the interaction term, *post*Acq*, shows that following the acquisition, including the year of the acquisition, the acquiring firm exhibits higher profitability as well as higher markups relative to the group of matched non-acquiring firms and relative to two years before the acquisition takes place.

Annex Table I.6. Firm M&As and Performance

	(1) Profit at t=0	(2) Profit at t=1	(3) Profit at t=2	(2) Markup at t=0	(4) Markup at t=1	(4) Markup at t=2
(Post * M&A)$_t$	0.025***	0.016**	0.029***	0.036***	0.032**	0.056***
	(0.006)	(0.007)	(0.008)	(0.013)	(0.016)	(0.018)
Post$_t$	-0.016***	-0.022***	-0.029***	-0.020*	0.005	-0.010
	(0.005)	(0.007)	(0.008)	(0.011)	(0.014)	(0.014)
Firm	Yes	Yes	Yes	Yes	Yes	Yes
Country-Industry(2-digit)-Year	Yes	Yes	Yes	Yes	Yes	Yes
Number of Observations	16,007	14,608	13,463	10,673	9,660	8,912
R-squared	0.874	0.863	0.852	0.922	0.906	0.902

*** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at the firm level.
All regressions are based on sample of acquiring firm and matched non-acquiring firms and include firm and country-industry-year fixed effects.

ANNEX II. THE LERNER INDEX: DEFINITION AND EXPECTED IMPACT OF MONETARY POLICY[7]

The Lerner Index is a (very) commonly used measure of market power. It is defined as:

$$Lerner = \frac{p - mc}{p} = 1 - \frac{mc}{p}$$

Where p is the ratio of revenue to quantity $Q_{b,t}$ (assets) and marginal costs are:[8]

$$mc = \frac{\partial C_{b,t}}{\partial Q_{b,t}} = \varepsilon_{b,t} \frac{C_{b,t}}{Q_{b,t}}$$

with $\varepsilon_{b,t}$ indicating the elasticity of costs to quantity.

This elasticity is estimated from a trans-log cost function:

$$logC_{b,t} = \alpha\ logQ_{b,t} + \frac{\delta}{2}\ logQ_{b,t}{}^{2} + \sum_{j=1}^{J} \beta_j\ w_{j,b,t}\ logQ_{b,t} + \sum_{j=1}^{J} \sigma_j\ w_j + \sum_{j=1}^{J}\sum_{k=1}^{J} \sigma_{jk}\ w_{j,b,t}\ w_{k,b,t} + \gamma X_{b,t} + \mu_b + \pi_t + \epsilon_{b,t}$$

where

- the w_j is a set of bank-specific input costs (in logs): total interest expenses over deposits, personnel expenses over assets, and other operating expenses over assets,
- $X_{b,t}$ is a set of bank-level time-varying controls to account for banks' capitalization (equity over assets), focus on lending (loans to assets) and loan quality (NPLs over loans),
- μ_b and π_t are bank and year fixed effects.

The equation is estimated by OLS separately for each country (thus all parameters are country-specific).[9] The elasticity is calculated as:

$$\varepsilon_{b,t} = \alpha + \delta\ logQ_{b,t} + \sum_{j=1}^{J} \beta_j w_{j,b,t}$$

[7] This annex was prepared by Deniz Igan, Maria Soledad Martinez Peria, Nicola Pierri, and Andrea Presbitero.

[8] Note that while c and q are the logs of costs and quantities, C and Q are the actual values.

[9] Imposing additional structure to the cost function, for instance homogeneity of degree one in input prices, does not significantly affect the results.

Then, the Lerner index can be expressed as:

$$Lerner = 1 - \frac{\varepsilon_{b,t}\frac{C_{b,t}}{Q_{b,t}}}{\frac{Income_{b,t}}{Q_{b,t}}} = 1 - \varepsilon_{b,t} * \theta_{b,t}$$

where $\theta = \frac{Costs}{Income}$.

Therefore, as long as $\varepsilon_{b,t}$ is fixed (or slow moving) over time, the Lerner increases when the cost to income ratio decreases, and vice-versa.

A measure of margins (on lending) commonly used by practitioners and policymakers is the Net Interest Margin, defined as:

Net Interest Margin (NIM) = Net Interest Income / Average Earning Assets

which can be written as

$$NIM = R_l - R_d$$

where R_l is the interest earned on assets, that is the ratio of gross interest income over assets, while R_d is the interest paid on liabilities, that is the ratio of interest expenses over assets.

While both NIM and Lerner aim to capture banks' margins, during the same period it is possible to observe Lerner going up but NIM being constant or decreasing.

To see this, notice that total costs are the sum of interest expenses and operating expenses, while income is the sum of interest and non-interest income.

$$\theta = \frac{Costs}{Income} = \frac{Interest\ Expenses + \ Opex}{Gross\ Interest\ Income + Non - Interest\ Income}$$

Ignoring operating expenses and non-interest income, it is possible to express the cost to income ratio as:[10]

$$\theta = \frac{Costs}{Income} = \frac{R_d}{R_l}$$

[10] Operating expenses and non-interest income are two important components of a bank's profits and losses statement. However, they are less affected by monetary policy. We ignore them for the sake of expositional brevity in order illustrate the role of a monetary expansions on NIM and Lerner index.

and the Lerner index as:

$$Lerner = 1 - \varepsilon * \frac{R_d}{R_l}$$

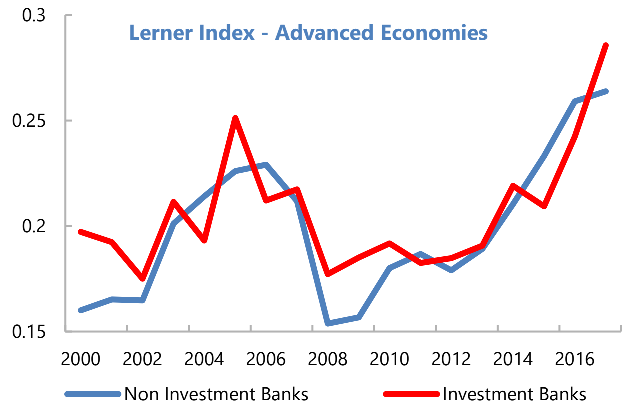
This formulation shows that, when interest rates move, the Lerner increases if the ratio of interest paid on deposits (and other liabilities) over the interest earned on assets decreases. Conversely, the NIM increases in the absolute value of the difference between these two interest rates. Hence, the Lerner moves with the ratio of the interest paid and received by banks, while the NIM moves with the differences between the two.

In advanced economies, the median interest paid by banks went down from approximately 2 percentage points (pp) to 0.5 pp., while the interest earned went down from 5.8 pp to 3.8 pp. Therefore, the NIM of a hypothetical bank experiencing these changes would decrease from 3.8 pp to 3.3 pp. The ratio of interest paid over interest earned would go from 0.34 to 0.13. Hence, the NIM of this bank would go down, while the Lerner index would go substantially up.

Moreover, the ratio is more problematic than the difference when interest rates are very low. In fact, when R_d approaches 0, and as long as banks charge a positive rate to their borrowers, then the ratio $\frac{R_d}{R_l}$ approaches zero, becoming uninformative.

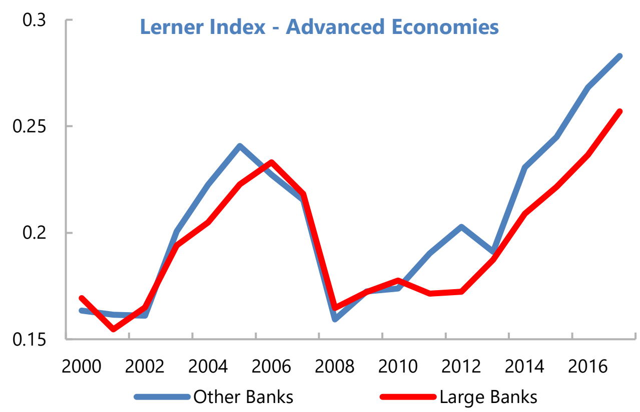
Annex Figure II.1: Lerner heterogeneity across bank groups

Investment vs Commercial Banks



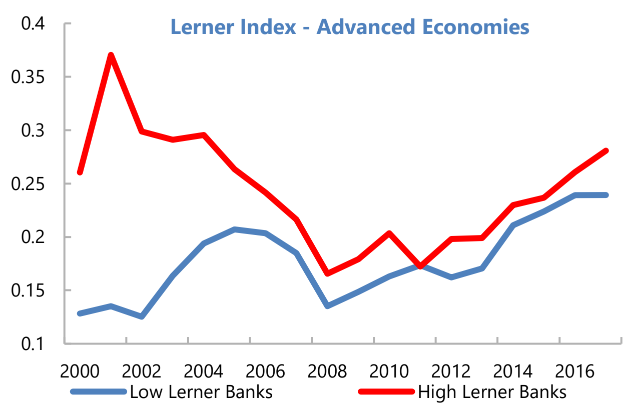
Source: Fitch Connect
Notes: Investment bank is defined as banks in the lowest decile of Loans to

Large vs Small Banks



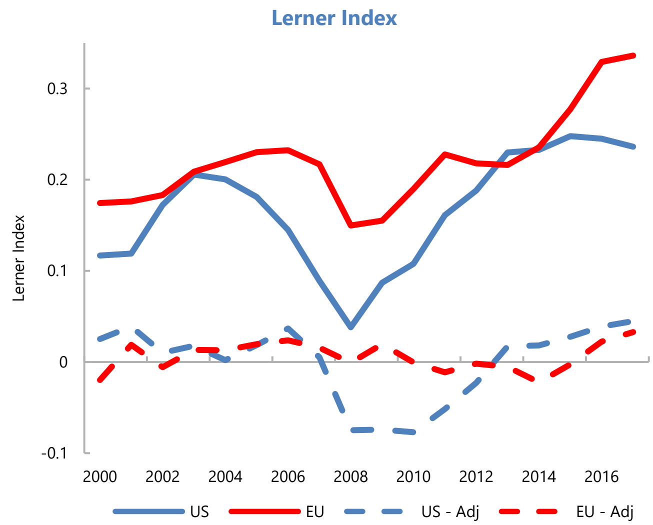
Source: Fitch Connect
Notes: Large bank is defined as banks in the lowest decile of asset size. 27 countries with more than 10 observations.

High vs Low Lerner Banks



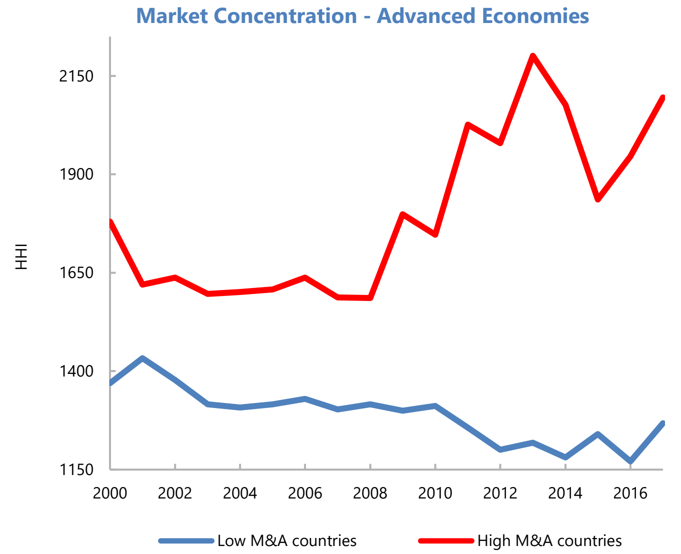
Source: Fitch Connect
Notes: High Lerner group is defined as banks in the lowest decile of Lerner in 2000-02. 27 countries with more than 10 observations.

Annex Figure II.2: Lerner heterogeneity across countries

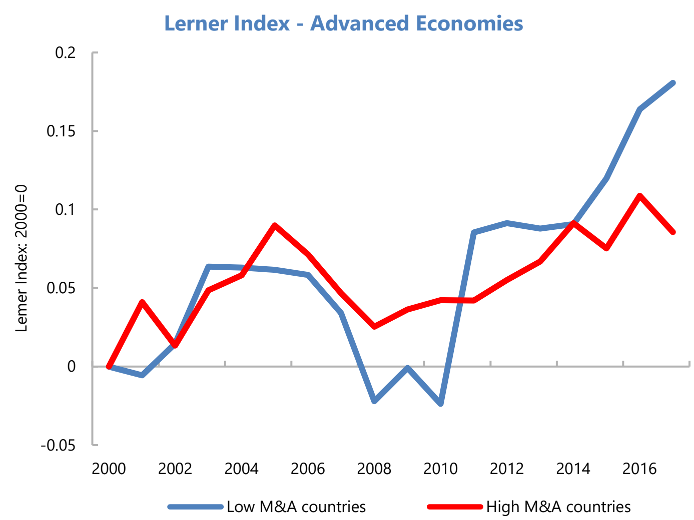


Sources: Fitch Connect, IFS and WEO.
Notes: US and 18 EU countries with more than 10 observations.

Annex Figure II.3: Concentration and Lerner across high and low M&A countries



Source: Fitch Connect.
Notes: 27 countries with more than 10 observations.



Source: Fitch Connect.
Notes: 27 countries with more than 10 observations.

Notes: High M&As countries are top 10 countries per number of M&As involving banks from 2008 to 2017, normalized by the average number of banks in the country

Annex Table II.1: Cyclical Drivers of the Lerner Index

	(1)	(2)	(3)	(4)
	Whole period		pre-GFC	post-GFC
Policy rate	-0.865***			
	(0.000)			
GDP growth	0.923***			
	(0.000)			
Policy Rate - AEs		-2.751***	-2.778***	-3.601
		(0.000)	(0.000)	(0.000)
Growth rate - AEs		1.499***	1.140***	1.661***
		(0.000)	(0.000)	(0.000)
Policy rate - EMDEs		-0.442**	-0.718***	0.438*
		(0.001)	(0.000)	(0.098)
Growth rate - EMDEs		0.973***	1.121***	0.520**
		(0.000)	(0.000)	(0.022)
Observations	1,108	1,108	582	525
R-squared	0.770	0.791	0.859	0.884
Within R-squared	0.166	0.241	0.296	0.188
Country FEs	Yes	Yes	Yes	Yes

Sources: Fitch Connect, World Economic Outlook, International Financial Statistics, national Central Banks, and IMF staff calculations.

Notes: the table reports the OLS estimation of country-year regressions of the Lerner index on contemporaneous and lagged GDP growth and policy rate, including country fixed effects. For each variable, each row reports the sum of the coefficients of the contemporaneous and lagged terms, and below that, in parentheses, the p-value of a joint F-test that the sum of the coefficients is different from 0. Columns (2) to (4) allow the effects of GDP growth and policy rate to differ across AEs and EMDEs. Columns (3) and (4) report separate regressions for the pre- and post-GFC, using 2010 as the first post-GFC year. Residual from the regression in column (2) are used to compute the statistically adjusted Lerner index. Robust standard errors. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

ANNEX III. ANALYZING FIRMS' LABOR MARKET POWER TRENDS IN ADVANCED ECONOMIES[11]

Recent literature finds some evidence of significant and rising power of firms in local labor markets, mostly for the United States (Azar and others, 2018; Benmelech, Bergman and Kim, 2018). Most studies measure firms' market power vis-à-vis their workers through concentration in local labor markets. Instead, this note seeks to measure labor market power through the sensitivity of workers' labor supply to the wage offered by their firm. To do so, as done recently by Hershbein, Macaluso and Yeh (2019) for the United States, the analysis extends the approach of De Loecker and Warzynski (2012) to estimate a firm's labor market power. In this set-up, a firm's labor market power reflects its ability to set the wage of its workers below their marginal productivity; the larger this so-called labor markdown is, the greater is a firm's labor market power vis-à-vis its workers, all else equal. The analysis uses Bureau van Dijk's Orbis database[12] and covers 18 advanced countries and eastern European emerging economies over 2000-2015 (excluding the United States due to lack of coverage of labor cost or employment data in Orbis). Three findings stand out:

- While there is no evidence that firms' labor market power—their labor markdown—has risen across the board, a small fraction of high-markdown firms experienced an increase (of about 3 percentage points) between 2000 and 2015.
- There are some signs that firms' power in labor and product markets are connected. Specifically, there is a U-shaped relationship between firms' labor markdowns and their product markups, implying that some of the most powerful firms in product markets also have some of the largest markdowns in labor markets. In addition, since the early 2000s, high-markup firms have increased their labor markdowns compared with other firms. Finally, larger firms have higher labor markdowns.
- There is wide heterogeneity in labor market power trends across industries. Labor markdowns have increased in manufacturing—driven by high-markdown firms—but they have declined in finance and insurance. The average increase in the labor market power of manufacturing firms over the sample of 18 countries studied here is qualitatively similar to, but quantitatively smaller than that obtained by Hershbein, Macaluso and Yeh (2019) for the United States.

These results should be interpreted with caution. In particular, the underlying methodology assumes that labor is a flexible production input and the production function does not change over time. It is also sensitive to any measurement error in the underlying data since changes in the labor markdown over time are essentially driven by changes in a ratio of two input shares—a variable input share and the labor income share, as explained below. Finally, the approach fails to

[11] This annex was prepared by Romain Duval, Guzman Gonzalez-Torres Fernandez, Davide Malacrino, Ippei Shibata and Yi Ji.

[12] Countries included in the Orbis dataset are Austria, Belgium, Bulgaria, Czech Republic, Germany, Estonia, Spain, Finland, France, Hungary, Italy, Korea, Norway, Poland, Portugal, Romania, Slovenia and Slovak Republic.

recognize worker heterogeneity within firms. For example, it might be that firms' average labor market power increased vis-à-vis their low-skilled workers but declined vis-à-vis their high-skilled workers, whose outside options have improved over time. Insofar as high-productivity high-markup firms tend to have a larger share of high-skilled workers, this might explain why only a U-shaped—rather than a simple, linear positive— relationship could be found in the aggregate firm-level data between firms' product markups and labor markdowns.

E. Approach used to measure labor market power

Loosely speaking, a firm's labor market power reflects its ability to set the working conditions of some or all of its workers, notably wages. In a fully competitive labor market, a firm would have to pay a worker her market wage at all times—offering a lower wage would lead the worker to take up a job at another firm, while offering a higher wage would be unnecessary since doing so would immediately attract a very large number of applicants. In a non-fully competitive labor market, a firm might lower its workers' wages without inducing all of them to leave the firm; in other words, the elasticity of labor supplied to the firm is finite, and the lower it is, the larger the firm's market power over its workers is, all else equal.

To formalize this insight, one can consider the static cost minimization problem of a firm that produces a single output using capital K, labor L, and other variable inputs V:

$$\Lambda(V, K, L, \lambda) = P^V V + rK + w(.)L - \lambda(Q(.) - Q)$$

Taking the first-order conditions with respect to variable input V and labor L and rearranging them yields:

$$\mu = \theta^V \frac{QP}{P^V V}$$

and

$$\mu = \theta^L \frac{1}{1 + \varepsilon_{w,L}} \frac{QP}{w()L}$$

where $\mu = \frac{P}{\lambda}$ represents the firm's markup in its output market, and $\theta^j = \frac{\partial Q}{\partial j}\frac{j}{Q}$ is the elasticity of output to input j. The elasticity of the wage to (residual) labor supply (the inverse of the labor supply elasticity), $\varepsilon_{w,L} = \frac{w()}{L}\frac{\partial L}{\partial w}$, constitutes the main object of interest and can be derived from these equations.

Note that, alternatively, one can consider a firm's profit maximization problem as in Hershbein, Macaluso and Yeh (2019):

$$\Lambda(V, K, L, \lambda) = PF(L, K, V) - w(L)L - rK - P^V$$

$$P\frac{\partial F(L, K, V)}{\partial \mathrm{L}} = \left[\frac{\frac{\partial w(L^*)}{\partial L^*}L^*}{w(L^*)} + 1\right] w(L^*)$$

$$= \left[1 + \varepsilon_{w,L}\right] w(L^*)$$

Therefore, $\varepsilon_{w,L}$ also captures the wedge between the marginal revenue product of labor and wage. As $\varepsilon_{w,L}$ increases, the firm has greater ability to set the wage below the marginal revenue product of labor, that is, it has more wage-setting power in the labor market.

Following De Loecker and Warzynski, (2012), we first estimate output elasticities θ^i (for $i \in (V, L)$) for each country-sector pair (at the Nace2 level) using the approach of Ackerberg and others (2015), and then calculate firm-level markups using firm-specific cost shares of material input V and labor input L, $\alpha^V = \frac{P^V V}{QP}$ and $\alpha^L = \frac{w()L}{QP}$. The measure of firm-level labor market power, $1 + \varepsilon_{w,L}$, can then be computed as follows:

$$1 + \varepsilon_{w,L} = \left(\frac{\theta^L}{\alpha^L}\right) / \left(\frac{\theta^V}{\alpha^V}\right)$$

F. Data

These measures of labor market power at the firm level are computed over the period 2000-2015 using cross-country firm-level data from ORBIS, as cleaned by Díez, Fan and Villegas-Sánchez (2019). The analysis covers 18 advanced and emerging economies for which the data on labor costs and material costs are available separately (rather than jointly as part of costs of goods sold): Austria (AT), Belgium (BE), Bulgaria (BG), Czech Republic (CZ), Germany (DE), Estonia (EE), Spain (ES), Finland (FI), France (FR), Hungary (HU), Italy (IT), Norway (NO), Korea (KR), Poland (PL), Portugal (PT), Romania (RO), Slovenia (SI), Slovak Republic (SK). We further clean the data by restricting the sample to observations with nonnegative estimated output elasticities and dropping potential outliers with product markups and labor markdowns in the top 0.01 percent of the distribution.[13]

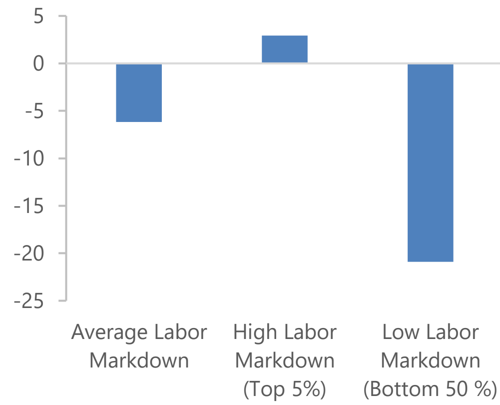
G. Results

Labor market power trends across different firms

Across all firms in the sample of 18 countries, the (firm-revenue-weighted) average labor markdown is found to have declined during 2000-15 (Annex Figure III.1). At the same time, trends in labor markdowns have been highly uneven across firms. High-markdown firms—the top 5 percent of firms with the highest average degree of labor market power, as measured by their average labor markdown over the sample period—have increased their markdown by about 3 percent on average, while low-markdown firms (the bottom 50 percent of the cross-country cross-firm distribution of markdown levels) have lowered theirs by about 20 percentage points during 2000-2015.

[13] We also test for robustness to restricting the sample only to firms with more than 20 employees and find the main findings to be robust.

Figure III.1. Labor market power trends across firms with different labor markdown levels
(cumulative change in percent)



Source: Orbis and Authors' calculations.
Notes: Bars depicts changes in labor markdown between 2000 and 2015, revenue-weighted average across all firms within each group.

Market power in labor and product markets

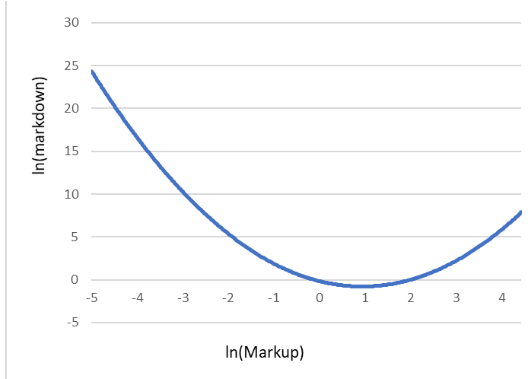
Bearing in mind the methodological limitations mentioned above, there is a U-shaped relationship between firms' power in labor and product markets, that is, between their product markups and labor markdowns. There is also some tentative evidence that high-markup firms (in the top five percent of the distribution of markup levels) have increased their labor markdowns relative to other firms, consistent with the view that they may have strengthened their labor market power (Annex Table III.1, Annex Figure III.2, and Annex Figure III.3). Also, larger firms—which generally tend to have a larger footprint in local labor markets—have higher labor markdowns than others (Annex Figure III.4).

Annex Table III.1 Non-linear relationship between markdowns and markups: econometric analysis results

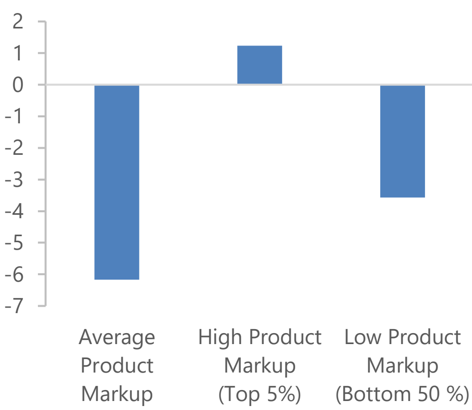
Dependent Variable	Residual ln(Markdown) (1)	(2)	Residual ln(Markdown) (1)	(2)
	Cross Section		Within	
Residual ln(Markup)	-1.21***	-1.48*	-1.41***	-1.78***
	(0.0024)	(0.0037)	(0.0034)	(0.0057)
Residual ln(Markup Squared)		0.714***		0.740***
		(0.0056)		(0.0086)
Constant	0.000	-0.027	-0.006	-0.024
	(.0005)	(.00053)	(.00002)	(.00025)
Cluster	Firm Level	Firm Level	Firm Level	Firm Level
Firm Fixed Effects	No	No	Yes	Yes
No of Observations	18,835,863	18,835,863	18,024,352	18,024,352

Source: Orbis and Authors' calculations.
Notes: Residual ln(Markdown) and Residual ln(Markup) were obtained as residuals from the regressions on Country x Year x Sector fixed effects. Values in parentheses are robust standard errors clustered at firm level.

Annex Figure III.2 Non-linear relationship between markdowns and markups

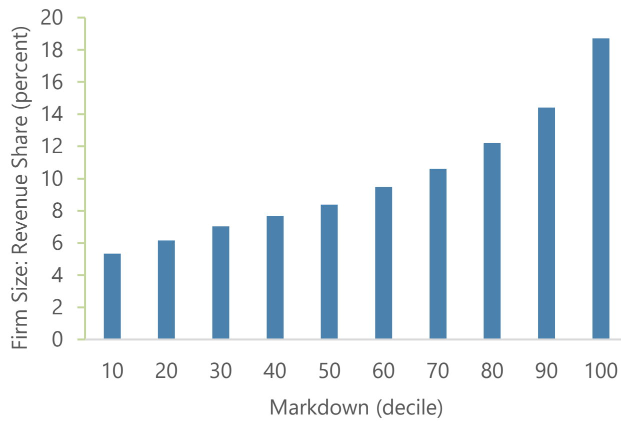


Annex Figure III.3. Labor market power trends across firms with different product markup levels
(cumulative percent change)



Source: Orbis and Authors' calculations.
Notes: Bars depicts changes in labor markdown between 2000 and 2015, revenue-weighted average across all firms within each group.

Figure III.4. Relationship between labor market power and firm size
(in percent)



Source: Orbis and Authors' calculations.
Notes: Bars depicts firms' revenue share within narrowly defined sector (Nace2) x year x country cell by decile of labor markdown.

Heterogeneity in labor market power trends across industries

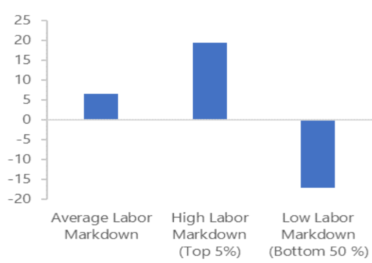
Labor market power trends have been heterogenous not only across firms but also across industries (Annex Figure III.5). While the average labor markdown rose in the manufacturing sector between 2000 and 2015, it declined somewhat in Information, communication and technology and, more markedly, in finance and insurance. Within manufacturing, high-markdown firms appear to have increased their labor markdown—that is, their labor market power—compared with other firms. The increase in labor markdowns obtained in manufacturing is qualitatively consistent with, but quantitatively smaller than, that found by Hershbein, Macaluso and Yeh (2019) for the United States. The decline in finance and insurance is qualitatively consistent with the notion that a fraction of highly-paid workers may have strengthened their bargaining power within that industry.

Annex Figure III.5. Labor market power trends across selected industries

(Change in labor markdown between 2000 and 2015 for three selected industries, revenue-weighted average across all firms within each group, in percentage points)

Annex Figure III.5.1 Labor market power trends across firms with different labor markdown levels: Manufacturing

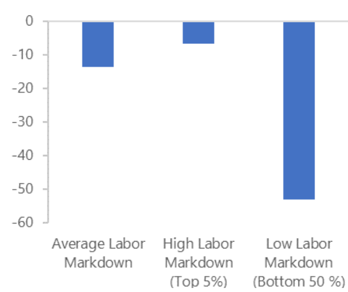
(cumulative percent change)



Source: Orbis and Authors' calculations.
Notes: Bars depicts changes in labor markdown between 2000 and 2015, revenue-weighted average across all firms within each group.

Annex Figure III.5.2. Labor market power trends across firms with different labor markdown levels: ICT sector

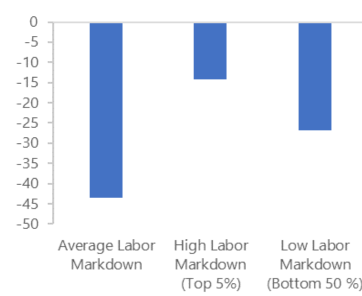
(cumulative percent change)



Source: Orbis and Authors' calculations.
Notes: Bars depicts changes in labor markdown between 2000 and 2015, revenue-weighted average across all firms within each group.

Annex Figure III.5.3. Labor market power trends across firms with different labor markdown levels: Finance & Insurance

(cumulative percent change)



Source: Orbis and Authors' calculations.
Notes: Bars depicts changes in labor markdown between 2000 and 2015, revenue-weighted average across all firms within each group.

APPENDIX IV. MARKET POWER AND MONETARY POLICY TRANSMISSION – AN EMPIRICAL APPROACH[14]

Recent studies have documented the rise in market power across firms (De Loecker and Eeckout, 2017, 2018; Diez et al. (2018), IMF WEO April 2019, Chapter 2). These studies have also found that markup levels and their increase are heterogeneous across firms in the economy, even within given industries. Specifically, high-markup firms have increased their markups much more than low-markup firms. High market power can affect monetary policy by reducing its transmission through two main channels:

- Demand Elasticity – High-markup firms face a less elastic demand curve, which reduces the sensitivity of their sales to changes in input costs, and consequently to monetary policy actions that affect input costs.

- Credit Constraint – The profits of a high-markup firm can help shelter it from shifts in external funding conditions (Aghion, Farhi and Kharroubi, 2019; Ahn, Duval and Sever, 2020).

This Appendix studies the implications of market power for the transmission of monetary policy by analyzing firms' responses to monetary policy shocks, conditional on market power, using Bureau Van Dijk's Orbis, a cross-country longitudinal firm-level database. Our sample consists of annual firm-level data covering fourteen advanced and selected (mostly central eastern European) emerging economies during the period 2001-2015. Monetary policy shocks are identified as the (country-time-level) forecast errors on policy rates that are orthogonal to forecast errors on GDP growth and inflation, following Furceri, Loungani and Zdzienicka (2018), among others, in the spirit of Auerbach and Gorodnichenko (2012). The response of different firms is estimated by applying the local projection method (Jordà, 2005), controlling for a rich set of fixed effects and firm characteristics (other than markups) to enable a causal interpretation of our results.

The key finding is that market power dampens the transmission of monetary policy actions, in line with theoretical priors. Specifically, we find that within a given country and industry, the output of high-markup firms responds less to monetary policy shocks than that of their low-markup counterparts. In addition, the difference between these responses is quantitively large. Further analysis provides evidence that high markups partly insulate firms from monetary policy shocks by providing product market rents and profits that ease firms' financial constraints. Overall, our results support the view that an increase in market power can reduce the effectiveness of monetary policy actions, partly by reducing the sensitivity of firms to changes in external financing conditions.

H. Methodology

[14] This annex was prepared by Raphael Lee and Marina M. Tavares based on Duval, Furceri, Lee, and Tavares (forthcoming)

Firm-level responses to monetary policy shocks are estimated using the local projection method (Jordà, 2005), which has two main advantages over alternatives such as an autoregressive distributed lag model. First, it is more robust to mis-specification (Ramey (2016)). Second, it is a parsimonious framework that is better suited for an analysis of interactions—in our case, between country-level monetary policy shocks and firm-level markups.

As a starting point, we estimate the response of firms' (log) real sales to a monetary policy shock, controlling for observed (time-varying) individual firm characteristics as well as firm, industry-year and year fixed effects. Real sales are computed by deflating a firm's nominal sales by the corresponding two-digit country-industry price deflator. Specifically, the estimated specification is:

$$\ln(y_{i,t+h}) - \ln(y_{i,t-1}) = \alpha_i^h + \alpha_t^h + \alpha_{s,t}^h + \beta_m^h \varepsilon_{c,t}^m + \Gamma^{h\prime} X_{i,t} + \varepsilon_{i,t+h} \qquad (1)$$

where i, c, s and t denote the firm, country, sector and year, respectively, $y_{i,t}$ denotes firms' real sales, $\varepsilon_{c,t}^m$ is the monetary policy shock constructed as described below, and $X_{i,t}$ is a set of firm-level controls that includes age, size (log of total assets) and financial variables (asset ratio, tangibility ratio, liability ratio and leverage ratio). Our object of interest is β_m^h, which measures the impact of a monetary policy shock that takes place in period *t* on firms' real sales in period *t+h*.

To identify the impact of market power on firms' response to monetary policy shocks, this basic specification is extended to allow for a differential response by firms of differing markup levels, which also incidentally enables us to tighten our identification strategy by controlling for all unobserved country-sector-year shocks. Specifically, based on the markup distribution across firms in year 2005, firms are put into three bins: bottom 25%, top 25% and middle (25-75%) of the distribution of markup levels. Markup levels are those used elsewhere in the Note, which are constructed following De Loecker and Warzynski (2012). Dummy variables for these markup bins are then interacted with the monetary policy shock variable to estimate IRFs by bins of markup level. This specification also enables us to control for country-industry-year fixed effects, and thereby to address a key source of potential omitted variable bias in (1). Since monetary policy shocks vary at the country-year level, the average firm response to a monetary policy shock is fully absorbed by the country-sector-year fixed effect, and the IRFs for each bin represent the difference between the response of the firms belonging to that bin and the average (unobserved) firm response. The estimated specification is the following:

$$\ln(y_{i,t+h}) - \ln(y_{i,t-1}) = \alpha_i^h + \alpha_{c,s,t}^h + \sum_{g \in G} \beta_{g,m}^h 1_{\mu_{i,t}} \varepsilon_{c,t}^m + \sum_{f \in F} \beta_{f,m}^h 1_{x_{i,t}} \varepsilon_{c,t}^m + \Gamma^h X_{i,t} + \varepsilon_{i,t+h} \quad (2)$$

where our object of interest is $\beta_{g,m}^h$, which measures the impact at horizon *t+h* of a monetary policy shock taking place in period *t* for firms belonging to markup bin $g \in G$. $\beta_{f,m}^h$ measures the impact of a monetary policy shock for firms belonging to bins $f \in F$ of a particular firm-level control variable—for example, age, as will be discussed further below.

I. Data

Monetary policy shocks

Monetary policy shocks are identified using the approach followed by Furceri, Loungani and Zdzienicka (2018), among others, in the spirit of Auerbach and Gorodnichenko (2012). Under this approach, monetary policy shocks are computed as the forecast error on policy rates. To ensure that this forecast error reflects unpredicted monetary policy decisions rather than predictable responses to shocks to economic activity and inflation, it is purged from forecast errors on GDP growth and inflation. To do so, we use forecasts from *Consensus Economics*. For policy rates—proxied by short-term nominal rates, forecast errors are computed as the difference between actual policy rates at the end of the year and those reported in *Consensus Economics* in October of the same year. Specifically, monetary policy shocks are constructed in two steps:

- Compute forecast errors for macroeconomic variable *j* in country *c*:

$$FE_{c,t}^{j} = \underbrace{\{A_{c,t}^{j}\}}_{Actual\ Value} - \underbrace{\{F_{c,t}^{j}\}}_{Forecast\ Value}$$

- Regress forecast error in policy rate *(rate)* on that GDP *(y)* and inflation *(p)*

$$FE_{i,t}^{rate} = \alpha_i + \beta_i FE_{i,t}^{y} + \gamma_i FE_{i,t}^{p} + \varepsilon_{i,h}^{m}$$

where $\varepsilon_{i,h}^{m}$, our monetary policy shock measure, corresponds to the unexpected change in the policy rate that is orthogonal to unexpected changes in GDP growth and inflation.

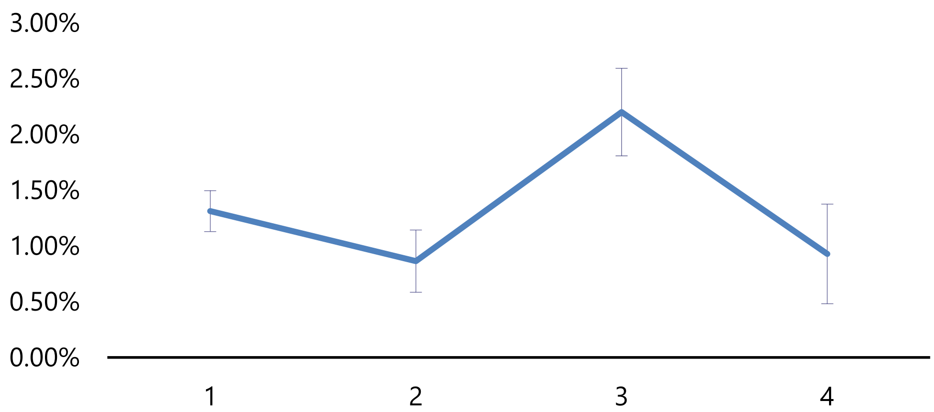
Firm-level data

Firms' real sales are computed over the period 2001-2015 using (unconsolidated) cross-country firm-level data from Orbis, covering 14 advanced and selected emerging economies for which we can draw cleaned data on markups, real sales and financial variables from Díez, Fan and Villegas-Sánchez (2019): Czech Republic (CZ), Germany (DE), Spain (ES), France (FR), United Kingdom (GB), Hungary (HU), Italy (IT), Japan (JP), Korea (KR), Netherlands (NL), Poland (PL), Slovak Republic (SK), Turkey (TR), and United States (US). We further clean the data by dropping potential outliers with markups in the top and bottom 0.01 percent of the distribution. Our final sample consists of 339 296 firms and 2 200 067 observations.

J. Results

As a start, we estimate equation (1) and find, in line with a broad macroeconometric literature and more recent microeconometric evidence, that firms' average real sales increase after a monetary policy cutting shock. An unexpected decrease in the policy rate increases cumulative growth of sales when controlling for financial variables, age, size and fixed effects (Annex Figure IV.1). The estimated response is roughly consistent quantitatively with those found in the literature, with a 100 basis points decrease in the policy rate being associated with about a one percent increase in real sales after three years.

Annex Figure IV.1. Output response to 100 basis points cut in the monetary policy rate
(deviation of firm's output (real sales) response from its country-industry average, in percent)



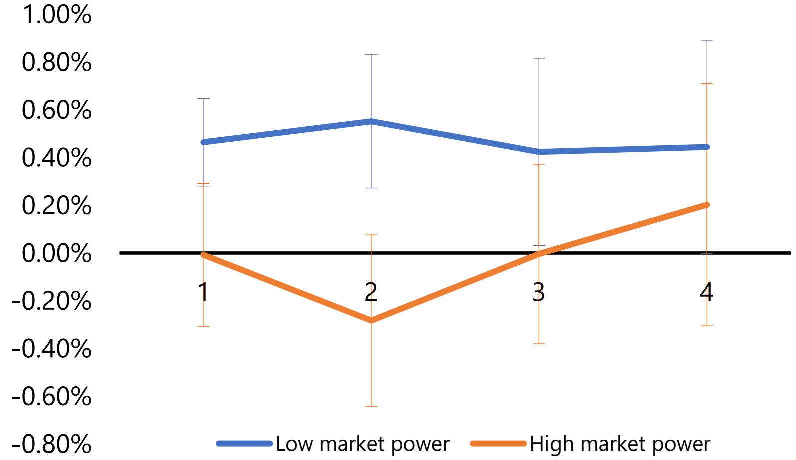
Source: IMF Staff Calculations
Note: x-axes in years; $t=1$ is the year of the shock. The shock represents a monetary policy shock that cannot be explained by forecast errors for growth and inflation; the lines denote the average impact of monetary policy shock on output.

We then distinguish high- from low-markup firms and estimate the impact of the same monetary policy shock on (log) real sales as per equation (2). As expected, high-markup firms respond less to monetary policy actions than their low-markup counterparts within the same country and industry (Annex Figure IV.2)—keeping in mind that the average response within each country and industry is absorbed by the country-sector-time fixed effects in (2). The difference in responses between high- and low-markup firms is also sizeable and statistically significant. This finding holds equally for monetary policy rate hikes and cuts, and it is robust to controlling for interactions between monetary policy shocks and the observed firm characteristics featured in our specification, as well as to using alternative markup bins and dropping any specific country or industry (for details, see Duval, Furceri, Lee and Tavares, forthcoming).[15] The main implication of these results is that increased market power across the economy, whether driven by higher markups within firms or an increase in the market share of high-markup firms, can reduce the effectiveness of monetary policy actions.

[15] Since we have to deflate a firm's sales by a country-industry-level deflator to obtain real sales, it could be *a priori* the case that the smaller response of high-markup firms to a monetary policy tightening shock may reflect a smaller price response rather than a smaller quantity response—for example, high-markup firms may cut their prices less than their low-markup counterparts. In practice, however, we do not find any significant difference in the response of markup levels to monetary policy shocks between high- and low-markup firms, which suggests that the difference in the responses of their real sales reflects a difference in the responses of quantities.

Annex Figure IV.2. Output response to 100 basis points cut in the monetary policy rate: high- and low-markup firms

(deviation of firm's output (real sales) response from its country-industry average, in percent)



Source: IMF Staff Calculations

Note: x-axes in years; *t=1* is the year of the shock. The shock represents a monetary policy shock that cannot be explained by forecast errors for growth and inflation; the lines denote the differential impact in percent between an average firm and a firm with markup at top 25 percent and bottom 25 percent of the markup distribution.

Finally, we extend the analysis to shed light on the channel(s) through which market power affects a firm's response to monetary policy actions. In particular, we provide evidence that high markups provide a buffer to credit-constrained firms, making them less sensitive to monetary-policy-driven shifts in external funding conditions. Specifically, we investigate whether high markups dampen the response of output to monetary policy shocks more for firms that are more credit-constrained. One set of firms that are typically more credit-constrained than others is younger firms.[16] To explore whether a high markup mitigates the response to monetary policy shocks more for younger firms than it does for older ones, we extent our specification to allow for an interaction between markup and age:

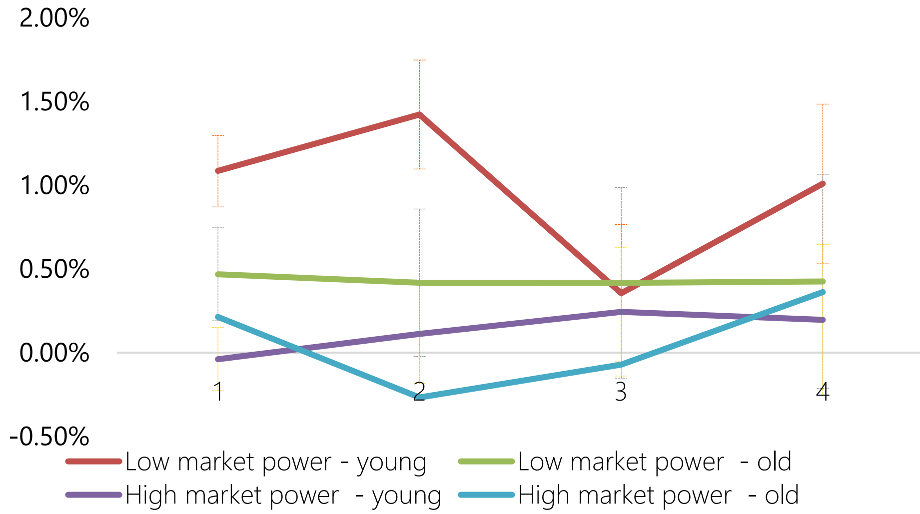
$$\ln(y_{i,t+h}) - \ln(y_{i,t-1}) = \alpha_i^h + \alpha_{c,s,t}^h + \sum_{g\in G}\sum_{f\in F} \beta_{g,m}^h 1_{\mu_{i,t}} \beta_{f,m}^h 1_{x_{i,t}} \varepsilon_{c,t}^m + \Gamma^h X_{i,t} + \varepsilon_{i,t+h} \qquad (3)$$

Where $f \in F$ denotes groups of firms by their age (above/below the median age of total distribution). Estimation results, which are summed up in Annex Figure IV.3, indicate that young high-markup firms respond less to monetary policy actions than young low-markup firms (purple line versus red line), while the difference in response between high- and low-markup firms is not statistically significant among older firms, most strikingly after two years. This finding implies that a high markup mitigates the response of output to monetary policy shocks more for younger firms, which are typically more credit-constrained than their older counterparts. This supports the view that market power dampens the impact of monetary policy decisions on firms in part by easing credit constraints.

[16] Related to this, Cloyne and others (2018) find on a sample of U.S. and U.K firms that younger firms' investment is far more responsive to monetary policy shocks than older firms' investment.

Annex Figure IV.3. Output response to 100 basis points cut in the monetary policy rate: high- versus low-markup and young versus old firms (right)

(deviation of firm's output (real sales) response from its country-industry average, in percent)



Source: IMF Staff Calculations

Note: x-axes in years; *t=1* is the year of the shock. The shock represents a monetary policy shock that cannot be explained by forecast errors for growth and inflation; the lines denote the differential impact in percent between an average firm and a firm with markup at top 25 percent of the markup distribution, young and old and a firm at the bottom 25 percent of the markup distribution. Where young firms are defined as the 25 percent younger and old firms are defined as the 25 percent older.

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