Market Power in an Emerging Market Economy: Evidence from Philippine Publicly Listed Corporations

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Abstract: This study investigates market power trends in an emerging market and developing economy (EMDE), the Philippines, by estimating markups for non-financial publicly listed corporations from 2001 to 2019 using a production-based methodology. While corroborating certain findings from advanced economies (AEs) regarding the positive relationship between firm size and markups, as well as markups and profitability, the substantial role larger firms play in markup movements, and the significant inter-sectoral variation in markups, this study reveals key distinctions. Notably, unlike AEs, the Philippines exhibits a more stable aggregate markup trend with limited evidence of consistent upward trend, potentially attributable to the heightened sensitivity of Philippine firms to macroeconomic fluctuations. This is further evidenced by the negative co-movement between markups and macroeconomic variables, such as interest rates and exchange rates. This study significantly contributes to the limited body of literature on market power in EMDEs by providing novel evidence from the Philippines and extending existing research on Philippine markups. These findings provide crucial insights for Philippine policymakers in enabling the development and implementation of more effective competition and antitrust policies to address market power dynamics and foster a more competitive landscape.

Keywords: Emerging market and developing economies, market power, markup, Philippines, production-based method
JEL classification: L11, L16

1. Introduction

It has been a long-standing belief that to maintain a healthy economy, competition among firms must be encouraged. However, weak competitive environments abound, allowing firms to obtain market power and set prices to the detriment of consumers. While market power can yield benefits like cost efficiencies and incentivise investments and innovation (Cavalleri et al., 2019; Church & Ware, 2000; Díez et al., 2019), its potential societal costs, including reduced consumer welfare, stifled innovation and investment, rent-seeking behaviour, and inefficient resource allocation (Cavalleri et

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al., 2019; Church & Ware, 2000; De Loecker & Eeckhout, 2018; De Loecker et al., 2018; De Loecker et al., 2020), necessitate government intervention. To promote a more equitable wealth distribution and address the welfare implications of decreasing competition due to rising market power, government must institute policies that curb its undesirable effects on efficiency and resource allocation.

Market power allows firms to price above their marginal cost, typically expressed in higher markups (i.e., the ratio of price to marginal cost). Markups indicate a firm's pricing discretion, deviating from perfect competition where markup equals one. Undoubtedly, knowledge of markup trends at the firm and industry level is valuable in helping formulate competition policies.

At the macroeconomic level, markup plays an important role in the monetary transmission mechanism and how the economy responds to aggregate demand shocks. This is because firms make pricing and/or production decisions based on how these shocks affect their profit maximising markups. The challenge for industrial organisation researchers is to develop measures of aggregate markups for the whole economy from micro-data.

The rising market power of corporations recently observed in advanced economies (AEs) is a concern of policymakers because of its implications on their economies' wellbeing. Recent cross-country studies at the International Monetary Fund (IMF) (Díez et al., 2018, 2019, 2021) show an upward trend of market power in selected AEs and emerging market and developing economies (EMDEs). Several country studies, like those for Belgium and the United Kingdom, show varying rates of increase in markups over time (see De Loecker et al., 2018; Haldane et al., 2018). De Loecker et al. (2020) reported an increasing trend in the sales weighted average markup rate for firms in the United States (US) from 1.21 in 1980 to 1.61 in 2016. This was after a steady decline from an average of 1.34 in the 1960s. This notable shift in trend over time appears to show the evolution of market structures towards less competition in these economies.

It is unclear if the same trend in rising market power can be seen in EMDEs, since the analysis of markups in EMDEs has typically been within the context of broader multi country studies, except for a study on Poland (Gradzewicz & Mućk, 2019) and Pakistan (Jamil et al., 2023). As of this writing, there appears to be little or no evidence of a prevalent rising pattern of movement in markup rates in EMDEs. In fact, the Poland study shows declining markup rates, which the authors attribute to globalisation and the emergence of global value chains (Gradzewicz & Mućk, 2019). The Pakistan study, meanwhile, shows that firm level markup in its textile sector remained unchanged with changes in trade policies, because its exports are homogeneous, low differentiated products (Jamil et al., 2023).

Studies in AEs attribute the upward trend in markups mainly to the technological prowess of firms and the birth of a few dominant ones resulting from mergers and acquisitions over time (see Akcigit et al., 2021). It is unlikely that the factors driving markup trends in EMDEs are identical to those in AEs, simply because the technological skills of the AEs' workforce are lacking in EMDE labour. Discoveries and innovations, resulting from research and development (R&D) activities by firms in AEs, allow the creation of new products and confer temporary monopoly power to the innovating firms.

In EMDEs, however, R&D are activities not normally pursued by domestic firms, and innovation can hardly be a cause of markup trend movements in most of these countries. Changes in the economic environment due to several factors other than technological advances are arguably a more plausible explanation for the movement of markups in EMDEs. Prior studies suggest several reasons for the general markup movement, with little agreement, such as rising fixed and sunk costs, growing value of network effects and intangibles, expanding globalisation and international linkages, and the like.

Additionally, a glaring difference between AEs and most EMDEs is the presence of weak institutional structures that fail to support market stability and encourage competition in EMDEs. As such, reasons like rising monopsony power, particularly in labour markets, increasing rent seeking through such actions as price discrimination and lobbying, growing anticompetitive product market regulations, and weakening antitrust enforcement seem more plausible explanations for the markup movement in EMDEs.

Given the significant gap in the existing literature, this study examines the market power in the lesser studied EMDEs and offers a novel institutional context, the Philippines. The Philippines is a modestly sized and growing economy, with nominal gross domestic product of USD402 billion (as of 2022), and an average GDP growth rate of approximately 5.5% since the turn of the century until before the COVID-19 pandemic hit (IMF, 2022). The country embraced trade liberalisation beginning in the 1980s, but the prior period's (post-World War 2) policy of protectionism and import substitution had already led to high levels of industry concentration (Aldaba, 2003). Prior industrial economics studies confirmed these, with findings of high concentration and market power in the Philippines' manufacturing industries (Aldaba, 2003; Go et al., 1999). Furthermore, the high level of wealth and resources concentrated in a few families and business groups, coupled with a prevalence of interlocking directorship among these large companies, do not necessarily encourage a competitive environment (Aldaba, 2003).

Prior to the enactment of Republic Act (RA) No. 10667 in 2014, also known as The Philippine Competition Act of 2014, and its resulting governing body, the Philippine Competition Commission, a comprehensive competition policy was non-existent. Philippine laws on antitrust that govern specific industries are fragmented and housed in various codes and laws and are not overseen by any one government body. Additional laws have since been passed or amended that allow and/or increase limits on foreign ownership and competition in certain sectors, such as retail, airports, expressways, telecommunications, among others (i.e., RA No. 11595, An Act Amending the Retail Trade Liberalization Act of 2000, and RA No. 11659, An Act Amending the Public Service Act). These are recent developments, and a thorough assessment of their impact is needed.

Employing a production-based methodology pioneered by De Loecker and Warzynski (2012), this study investigates market power trends at the aggregate and sectoral levels utilising financial statement data from non-financial Philippine publicly listed corporations (PLCs) spanning the period 2001 to 2019. The analysis reveals an average aggregate markup of 1.70, with upward and downward movements over this period – peaking in 2005 and bottoming out in 2013. Since 2013, the aggregate markup has demonstrated relative stability, reaching 1.68 in 2019, contrasting with the upward trends observed in AEs. This stability may be attributed to the heightened sensitivity of Philippine firms to macroeconomic fluctuations, as evidenced by the negative co-movement between markups and macroeconomic variables (i.e., interest rates and exchange rates). Meanwhile, consistent with findings from AEs, this study observes: a positive relationship between firm size and markups, as well as markups and profitability (measured as economic profit rate (π rate) and return on assets (ROA)), the substantial role larger firms play in markup movements, and the significant inter-sectoral variation in markups. Furthermore, the analysis indicates a shift towards a greater proportion of high markup firms in 2019 compared to 2001.

This study significantly contributes to the empirical study of imperfect competition using the most recent methodological approach to market power, production-based estimation of markups using firm level data. It expands the limited body of literature on market power in EMDEs, by offering a novel institutional context, the Philippines. It updates and broadens existing research on markups in the Philippines (Aldaba, 2003; Go et al., 1999), by providing Philippine baseline estimates of market power/markup trends at the aggregate and sectoral level. It also goes beyond markup evolution by being one of the few studies in EMDE, and the only one in the Philippines, that compare markups with other performance indicators, providing a more nuanced understanding of the relationship between markups and profitability, and with macroeconomic indicators, acknowledging that firm pricing decisions to preserve its markup can largely be influenced by a country's macroeconomic environment. This study's findings provide crucial foundations for policymakers to develop and implement effective competition policies and antitrust regulations at the sectoral/industry level to help promote industry competition.

The remainder of the paper proceeds as follows. Section 2 provides a review of the relevant literature, commencing with a discussion on market power and its various measurements, particularly markups, and concludes with an examination of existing research on markup. Section 3 outlines the methodological approach employed in this study, detailing the production-based estimation of markups and providing a description of the data sources used in the analysis. Section 4 presents empirical results, highlighting key findings such as the mean and standard deviations of markups, the evolution of markups over time, and their distributional characteristics. Section 5 delves into the estimation results, examining the relationships between markups and other key variables, including firm performance measures (i.e., π rate and ROA) and macroeconomic factors (i.e., interest rates and exchange rates). Finally, Section 6 concludes the paper by summarising the key findings, discussing their implications for policymakers, acknowledging study limitations, and outlining avenues for future research.

2. Review of Literature

Competition is necessary for a well-functioning economy (De Loecker & Eeckhout, 2018), yet very few markets correspond to this theoretical case (Calligaris et al., 2018). Instead, imperfect competition abounds, distorting the mechanism of an efficient economy and allowing firms to exercise market power over consumers.

The implications of market power are not straightforward. The negative view is that market power has societal costs: redistributes resources from workers and consumers to firm owners, reduces welfare and consumers' well-being by constraining outputs and increasing prices, stifles innovation and investment, encourages rent-seeking behaviour, and introduces inefficiencies in the allocation of resources and production between firms (Cavalleri et al., 2019; Church & Ware, 2000; De Loecker & Eeckhout, 2018; De Loecker et al., 2018; De Loecker et al., 2020). Yet, market power is also believed to contribute certain benefits: achieves cost efficiencies due to scale economies, and incentivizes investments and innovation (Cavalleri et al., 2019; Church & Ware, 2000; Díez et al., 2019). Either way, the societal costs provide sufficient economic rationale for intervention from various government branches – from competition and antitrust policy, trade and tax policy, and even monetary policy – to constrain the exercise of market power (Church & Ware, 2000; De Loecker & Eeckhout, 2018).

2.1 Markup as a Measure of Market Power

Market power can be identified and measured in many ways, as can be gleaned from the numerous papers written on this topic. Perloff et al. (2007) provided detailed discussions on different methodologies and modelling techniques in analysing market power at the firm and industry level. A symposium with three papers published in the summer 2019 issue of the *Journal of Economic Perspectives* discussed more recent developments on the topic (Basu, 2019; Berry et al., 2019; Syverson, 2019).

Early measures, such as the concentration ratio derived from market shares and used in the structure-conduct-performance literature, have been determined as an inadequate measure of market power due to conceptual problems stated in Perloff et al. (2007), Berry et al. (2019) and Syverson (2019). Most modern measures associate market power with the markup of the price of a good over its marginal cost of production. Commonly expressed as a ratio, $\mu = P/MC$, the markup can only indicate if a firm or industry is competitive ($\mu = 1$) or not, and, by itself, gives no information about the structure of the market. A larger markup, however, implies greater market power.

The most utilised method by researchers to estimate markup rates, according to Basu (2019), is the method of De Loecker and Warzynski (2012). It is a production-based method to estimate markups, which requires an estimate of the output elasticity of a single input. The idea is that marginal cost is the same for all inputs, and hence information on only one input is needed to estimate marginal cost. Econometric estimation of firm level production function parameters with endogenous productivity has been developed by industrial organisation researchers (e.g., Ackerberg et al., 2015; Levinsohn & Petrin, 2003; Olley & Pakes, 1996) and is done in this study to obtain estimates of the output elasticities. This method is used for this study because it utilises information available from firms' financial statements and does not rely on assumptions regarding demand and competitive behaviour. Since it requires fewer data inputs, it makes it more readily applicable in contexts with limited data availability, such as EMDEs. Most empirical studies using this method have shown markups to be increasing over time in AEs (e.g., Calligaris et al., 2018; De Loecker & Eeckhout, 2018; De Loecker et al., 2020; Díez et al., 2018, 2019, 2021; Haldane et al., 2018; Traina, 2018.)

2.2 Research on Markups

Empirical studies have shown markups increasing over time, with some studies showing more moderate increases (Calligaris et al., 2018; Díez et al., 2019; Díez et al., 2021; Traina, 2018) and other more significant increases (De Loecker & Eeckhout, 2018; De Loecker et al., 2020; Díez et al., 2018; Haldane et al., 2018). Several factors have been identified for these increases in markups, with little agreement (Berry, 2019; Calligaris et al., 2018, Cavalleri et al., 2019, Díez et al., 2019): rising fixed and sunk costs, increasing innovation and digitisation, growing value of network effects and intangibles, rising monopsony power particularly in labour markets, increasing rent seeking through such actions like price discrimination and lobbying, expanding globalisation and international linkages, weakening antitrust enforcement, and growing anticompetitive product market regulations. (See Berry et al. (2019) for further details.)

Apart from a few studies that show steady (Cavalleri et al., 2019; De Loecker et al., 2018) or even declining markups (Gradzewicz & Muck, 2019), markups have generally been rising. Though increases are seen across countries, sectors and firms, they are more evident in AEs (Díez et al., 2019; Díez et al., 2021), digitally intensive sectors (Calligaris et al., 2018; Díez et al., 2019), and firms already in the top decile (Calligaris et al., 2018; De Loecker et al., 2020; Díez et al., 2019; Díez et al., 2021) or quartile (Haldane et al., 2018) of the markup distribution.

An increase in markups may not always imply that firms have more market power (and higher profit) (De Loecker et al., 2020). Increasing markups may be driven by decreasing marginal costs and/or increasing fixed costs, caused by many reasons, such as increase in demand or its elasticities, changes in market structures and the like (De Loecker et al., 2020). Markups can overestimate market power in the presence of fixed costs, as firms need to recover these through markups to avoid losses (Díez et al., 2019). Whether markups increase profit depends on the pattern of overhead costs and other factors that impact a firm's cost structure (De Loecker et al., 2020). Nevertheless, empirical studies have shown a positive relationship between increasing markups and profitability (De Loecker et al., 2020; Díez et al., 2018).

3. Methodology

3.1 Production-based Estimates of Markup

This study employs De Loecker and Warzynski's (2012) production-based approach to estimate the output elasticity of the variable input used in the calculation of firm level markup rates. This methodology assumes that an input's share to total revenue is equal to its output elasticity only when the output price equals marginal cost. That is, the firm operates under competitive conditions, where price equals marginal cost. Deviation from marginal cost pricing indicates non-competitive firm behaviour.

To fix ideas, assume a cost minimising firm produces output, q_{it}, using a variable input, v_{it}, and fixed capital, k_{it}. The Lagrange for this problem is:

$$L = w_{it}v_{it} + r_{it}k_{it} + \lambda_{it}[\overline{q}_{it} - q_{it}(v_{it}, k_{it})] \quad (1)$$

where $\overline{q}_{it}$ is the given output level, while w_{it} and r_{it} are the price of the variable input and the user cost of capital, respectively. The firm chooses the variable input given the capital stock to minimise cost. The first order condition for the variable input, $w_{it} - \lambda_{it}(\partial q_{it}/\partial v_{it}) = 0$, can be multiplied through by v_{it}/q_{it} and rearranged to obtain an expression for the output elasticity of the variable input, θ_{it}^{v}:

$$\frac{\partial q_{it}}{\partial v_{it}}\left(\frac{v_{it}}{q_{it}}\right) = \frac{w_{it}}{\lambda_{it}}\left(\frac{v_{it}}{q_{it}}\right) = \theta_{it}^{v} \quad (2)$$

where λ_{it} is the marginal cost.[1]

Next, define the markup as the ratio of the output price, p_{it}, to marginal cost, $\mu_{it} \equiv p_{it}/\lambda_{it}$. Using (2) in this expression, the markup can be calculated as:

$$\mu_{it} = \theta_{it}^{v}\left(\frac{p_{it}}{w_{it}}\frac{q_{it}}{v_{it}}\right) = \frac{\theta_{it}^{v}}{\alpha_{it}^{v}} \quad (3)$$

where $\alpha_{it}^{v} \equiv w_{it}v_{it}/p_{it}q_{it}$ is the share of the variable input cost to the total value of output.

It is clear that $\mu_{it} = 1$ under perfect competition because of marginal cost pricing, that is, $p_{it} = \lambda_{it}$. In this case, the output elasticity in equation (3) is equal to the input's revenue share, $\theta_{it}^{v} = \alpha_{it}^{v}$. This is no longer true under imperfect competition because the markup drives a wedge between the price and marginal cost and therefore, $\theta_{it}^{v} \neq \alpha_{it}^{v}$.

Numerically calculating a firm's markup requires information on three variables: (1) total sales, (2) the cost of its variable input to calculate the revenue share of this input, and (3) the output elasticity, which can be derived by econometrically estimating the parameters of its production function. De Loecker and Warzynski (2012) estimate the production function parameters using a two-step procedure originally due to Olley and Pakes (OP) (1996). The method is designed to account for the effects of unobservable productivity shocks on the firm's demand for inputs, and thus addresses the endogeneity issue. The idea is that large positive productivity shocks induce firms to demand more inputs, and hence ordinary least square (OLS) estimation is inappropriate, for it will produce biased estimates.

Consider a Cobb-Douglas production function in logs:

$$q_t = \beta_0 + \beta_l l_t + \beta_k k_t + \epsilon_t = \beta_0 + \beta_l l_t + \beta_k k_t + \omega_t + \varepsilon_t \quad (4)$$

where ε_t is an unobservable shock to production that can represent potentially serially correlated measurement errors and/or unexpected occurrence of events affecting the firm's production. ω_t is the unobservable productivity shock that can be predicted by the firm when it makes its input decision.[2] If ω_t can be predicted or partially observed by the firm, the decision to hire inputs then partly depends on ω_t. Thus, OLS parameter estimates of (4) will be inconsistent.

The OP method proposes an investment policy function, $i_t = f_t(k_t, \omega_t)$, that can be used to proxy for productivity shock. Under the assumption of a strict monotonically increasing relationship between productivity shock and investment, one can invert the policy function, $\omega_t = f_t^{-1}(k_t, i_t)$, which can be used in (4):

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[1] λ_t, which is also the Lagrange multiplier, must be the same for all variable inputs at the optimum. Only one variable input is assumed to simplify exposition.

[2] This shock is unobservable to the econometrician but not necessarily to the firm. The firm index is omitted in the equations for ease of exposition.

$$q_t = \beta_0 + \beta_l l_t + \beta_k k_t + f_t^{-1}(k_t, i_t) + \varepsilon_t = \beta_l l_t + \phi_t(k_t, i_t) + \varepsilon_t \quad (5)$$

where $\phi_t(k_t, i_t) = \beta_0 + \beta_k k_t + f_t^{-1}(k_t, i_t)$ is treated non-parametrically.

This in effect replaces the unobservable shock, and the investment function is essentially used to control for unobserved productivity. In the first stage of OP, estimates of β_l and ϕ_t are derived from (4) using generalized methods of moments (GMM) and the moment condition is:

$$E(\varepsilon_t \mid I_t) = E(q_t - \beta_t l_t - \phi_t(k_t, i_t) \mid I_t) = 0 \quad (6)$$

It is assumed that the productivity shock follows a first order Markov process, $\omega_t = g(\omega_{t-1}) + \xi_t$. Using this in (4) and the estimated parameters – $\hat{\beta}_l$ and $\hat{\phi}_t$ – from the first stage, one obtains:

$$\begin{aligned} q_t &= \beta_0 + \beta_l l_t + \beta_k k_t + g(\omega_{t-1}) + \xi_t + \varepsilon_t \\ &= \beta_0 + \beta_l l_t + \beta_k k_t + g(\phi_{t-1}(k_{t-1}, i_{t-1}) - \beta_0 - \beta_k k_{t-1}) + \xi_t + \varepsilon_t \end{aligned} \quad (7)$$

From this, the moment condition used in the second stage estimation is obtained:[3]

$$\begin{aligned} E(\xi_t + \varepsilon_t \mid I_t) = E(q_t - (\beta_0 + \beta_l l_t + \beta_k k_t + \\ g(\phi_{t-1}(k_{t-1}, i_{t-1}) - \beta_0 - \beta_k k_{t-1})) \mid I_t) = 0 \end{aligned} \quad (8)$$

Several modifications to the original OP methods have been proposed. Levinsohn and Petrin (2003) (LP), which also uses a two-stage process, replace the investment function with the firm's intermediate input demand function, which when inverted yields the function to control for productivity: $\omega_t = f_t^{-1}(k_t, m_t)$. The concern of this study is based more on data availability since many firms report no investment at all, unlike intermediate inputs where a vast majority report usage of these inputs. Wooldridge's (2009) algorithm, adopted in this study, reworks the OP and LP methodologies to estimate the parameters more efficiently and to make the calculation of standard errors easier. His method uses the moment conditions derived from equations (4) and (5) to jointly estimate their parameters by GMM and does away with the two-step process. This method also avoids the functional dependence problems identified by Ackerberg et al. (2015) in the OP and LP methodologies. Wooldridge's (2009) method, as implemented by Rovigatti and Mollisi (2018), is used in this study with investment as the proxy.

3.2 Sources of Data

Annual financial statement data of 285 non-financial PLCs from 2001 to 2019 are sourced from Refinitiv Datastream/LSEG. The data is limited to pre-COVID-19 to avoid the pandemic's disruptive impact on output elasticity estimation, which is crucial for markup calculation. There is a high probability that the input-output relationships

[3] For a detailed exposition of this procedure, see Ackerberg et al. (2015) from which this discussion heavily draws. Note, the inverse of the investment policy function used to proxy for the productivity shocks is treated non-parametrically to avoid additional intensive computation if it is to be expressed as a solution to a dynamic programming problem.

observed during the COVID-19 period differ markedly from those observed in non-pandemic periods.

Two hundred sixty-one firms remain in the dataset after eliminating firms with less than three years of observations. The number of firms is further reduced to 212 after removing redundant entries and holding companies, as they do not engage in the production of goods or services. The financial statement variables used in the estimation of output elasticities and the calculation of the markups are the firm's sales, cost of goods sold (COGS), capital expenditures (CAPEX), and gross property, plant and equipment (PPEG).[4] These are converted to real terms by deflating them with the price deflators from the national income accounts. These prices obtained from the Philippine Statistical Authority (PSA) are the sectoral implicit price deflators, the producer price index, and the implicit price index for the gross fixed capital formation. Some financial statement variables used in this study are winsorized to remove outliers, and values identified as errors are removed (e.g., negative COGS). This study's final data set covers a 19-year period from 2001 to 2019, with 195 firms classified into 16 sectors. The sector classification is based on the Philippine Standard Industrial Classification (PSA, n.d.), a classification system patterned after the International Standard Industrial Classification issued by the United Nations Statistics Division.

One criticism of using data from PLCs is that small and medium scale firms, abundant in EMDEs, are not adequately represented in the dataset. Indeed, PLCs represent the largest firms in the Philippines, with total stock market capitalisation equivalent to about 75% of the country's GDP (as of 2020). However, this concentration does not hinder the analysis of market power, as these firms are most likely to possess it.

The sectoral prices used to convert nominal magnitudes to real are based on the sectoral categories of the national accounts constructed by the PSA. The macroeconomic and financial data used in this study, interest rates on government securities and exchange rates, are obtained from the Bangko Sentral ng Pilipinas.

4. Markup Calculations

Since firm markup is calculated as the ratio of the output elasticity of the variable input to its share in total sales, the Cobb-Douglas output elasticities are estimated for each of the 16 sectors. The estimates are obtained following Wooldridge's (2009) simplification of the two-step econometric OP method (1996). The one-step implementation of this procedure uses the Stata code from Rovigatti and Mollisi (2018). Table 1 shows the estimated coefficients of the variable input.

To view the general pattern of movements of the markup, the aggregate markup μ_t is calculated as the sales weighted average of firm level markups:

$$\mu_t = \sum_i m_{it} \mu_{it} \tag{9}$$

where $m_{it} = s_{it} / \sum_i s_{it}$ is the share of firm i sales in total sales in period t.

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[4] Capital expenditures include but are not limited to additions to PPE and investments in machinery and equipment. This study follows the literature in using COGS to measure a firm's variable inputs.

Table 1. Cobb-Douglas parameter estimates, 2001 to 2019

Sector	θ*	Standard error
Chemical products	0.852	0.027
Construction	0.859	0.027
Electric power	0.700	0.037
Financial services	0.452	0.043
Food and beverage	0.900	0.017
Gaming and recreation	0.845	0.036
Hotels and restaurants	0.599	0.031
Machinery and equipment	1.060	0.021
Media	0.834	0.061
Mining	1.094	0.048
Not elsewhere classified (NEC)**	0.778	0.028
Oil and oil products	0.933	0.033
Real estate	0.862	0.018
Technology products and services	0.659	0.054
Transport storage services	0.618	0.053
Transportation	0.721	0.039

Notes: * θ = Variable input. ** NEC is a catch-all category used for companies that do not fit existing categories or for companies with no peers, making industry markups impractical.

4.1 Mean and Standard Deviations of Markup

Table 2 presents the means and Table 3 the standard deviations of the dataset used in this study for the aggregate and individual sectors.

Both tables present financial and performance metrics, revealing significant inter-sectoral variations in these indicators. By focusing on sectors with extreme performance (highest and lowest) during the period 2001 to 2019 and comparing them to their respective standard deviations, insights are gained into sector-level stability and variability. For instance, the financial services sector has the highest π rate (M = 36.47) with moderate variability (SD = 21.84), indicating strong and relatively stable profitability. In contrast, the oil and oil products sector demonstrates the lowest π rate (M = -44.33) coupled with high volatility (SD = 209.54), reflecting low and unstable profitability. Similarly, the financial services sector displays the highest ROA (M = 18.49, SD = 13.18), suggesting efficient asset utilisation, while the gaming and recreation sector exhibits the lowest ROA (M = 2.39, SD = 6.49), indicating less efficient asset utilisation. Finally, the real estate sector exhibits the highest markup (M = 3.26) with moderate variability (SD = 0.59), implying strong market power, while the transportation sector displays the lowest markup (M = 1.01, SD = 0.14), suggesting weaker market power.

Further exploring the relationships between π rate and markup, as well as ROA and markup, reveals how market power moves with overall profitability and asset efficiency across different sectors. A positive relationship generally exists between π rate and markup, as exemplified by the financial services sector with both high π rate (M =

Table 2. Means of markup, 2001 to 2019

	Sales (PHP mn)	COGS (PHP mn)	CAPEX (PHP mn)	PPEG (PHP mn)	Total Assets (PHP mn)	π[1] (%)	π Rate[2] (%)	ROA[3] (%)	Markup[4]
Economy-wide	14,993.45	9,681.67	1,682.72	20,489.19	27,715.76	2,971.28	–1.69	8.39	2.06
Sectors									
Chemical products	2,023.03	1,467.88	150.38	3,301.62	3,531.54	260.08	3.99	3.95	1.25
Construction	13,716.84	8,724.23	1,465.20	18,691.30	25,100.97	3,685.97	1.71	6.79	1.34
Electric power	47,149.60	31,875.01	3,908.47	62,615.38	85,713.64	5,987.17	21.30	6.92	1.16
Financial services	1,748.47	677.66	168.38	1,157.48	7,446.99	1,002.78	36.47	18.49	2.52
Food and beverage	19,836.82	13,494.88	1,114.30	12,408.51	20,366.52	2,511.45	5.72	7.15	1.33
Gaming and recreation	891.62	432.46	71.27	1,088.55	2,854.93	336.01	3.91	2.39	2.06
Hotels and restaurants	11,740.64	7,604.80	1,330.14	10,800.35	14,514.99	2,582.47	13.18	11.69	1.44
Machinery and equipment	11,350.64	9,260.21	473.07	4,840.93	9,060.58	1,051.55	8.10	9.81	1.32
Media	10,388.80	4,991.82	945.44	13,474.92	16,343.42	3,750.48	21.93	17.39	1.81
Mining	4,802.19	2,213.01	1,148.55	12,893.87	14,238.71	1,564.27	–17.70	4.74	2.50
NEC	12,729.72	9,122.35	740.39	5,551.56	14,723.15	2,394.56	8.11	4.19	1.40
Oil and oil products	54,317.89	48,732.73	2,245.52	26,761.84	36,535.88	2,976.93	–44.33	6.19	1.06
Real estate	6,046.31	2,656.86	1,361.15	12,565.99	33,504.37	2,530.63	–12.30	11.99	3.26
Technology products and services	31,331.84	9,596.39	8,126.24	129,430.64	70,661.08	10,654.42	–10.04	3.53	3.09
Transport storage services	10,069.30	4,279.52	1,336.29	12,125.78	25,312.90	4,564.08	19.25	7.69	1.81
Transportation	28,298.53	22,394.41	4,625.38	48,032.19	41,977.05	1,430.55	10.98	6.37	1.01

Notes: [1] Economic profit, see equation 10; [2] Profit rate, see equation 11; [3] Return on assets = Economic profit/Total assets; [4] Markup, see equation 3. NEC – Not elsewhere classified.

Table 3. Standard deviations of markups, 2001 to 2019

	Sales (PHP mn)	COGS (PHP mn)	CAPEX (PHP mn)	PPEG (PHP mn)	Total Assets (PHP mn)	π[1] (%)	π Rate[2] (%)	ROA[3] (%)	Markup[4]
Sectors									
Chemical products	2,131.47	1,585.64	244.20	2,664.00	2,932.62	349.44	26.05	5.64	0.11
Construction	16,596.19	9,717.83	2,555.41	23,093.11	35,066.01	5,957.51	69.9	17.58	0.12
Electric power	78,076.13	60,705.97	5,876.42	78,297.45	102,922.99	7,908.32	18.33	5.97	0.12
Financial services	2,699.32	1,687.82	307.62	973.72	8,457.64	1,150.45	21.84	13.18	1.20
Food and beverage	36,621.22	24,261.85	2,840.99	21,727.14	35,801.26	5,840.70	14.63	14.07	0.06
Gaming and recreation	944.85	447.69	94.81	745.20	3,633.76	805.59	32.71	6.49	0.76
Hotels and restaurants	25,987.85	20,053.79	3,954.34	20,673.90	27,124.48	4,835.08	17.44	9.90	0.72
Machinery and equipment	13,136.19	11,562.59	683.42	4,050.36	10,313.80	1,494.99	10.94	15.14	0.03
Media	11,806.71	5,681.49	1,511.54	16,011.04	20,591.26	1,684.31	9.15	9.03	0.16
Mining	8,162.46	3,510.29	2,056.62	16,890.51	19,104.22	3,631.72	72.58	15.52	0.38
NEC	25,315.28	21,053.02	1,078.44	7,057.76	25,185.69	4,579.39	33.84	10.60	0.24
Oil and oil products	117,122.94	107,744.72	6,401.61	57,727.02	80,907.57	6,505.47	209.54	11.22	0.04
Real estate	16,959.37	7,935.64	5,162.52	41,441.52	82,933.24	7,113.98	240.75	189.75	0.59
Technology products and services	55,801.03	22,248.70	15,034.29	202,222.21	128,995.59	20,694.64	77.52	26.42	0.94
Transport storage services	14,287.82	5,348.79	2,451.48	20,964.02	49,587.74	7,749.13	20.93	15.41	0.46
Transportation	42,829.99	36,654.08	7,006.66	66,380.78	64,606.66	3,534.60	9.45	5.43	0.14

Notes: [1] Economic profit, see equation 10; [2] Profit rate, see equation 11; [3] Return on assets = Economic profit/Total assets; [4] Markup, see equation 3. NEC – Not elsewhere classified.

36.47) and high markup (M = 2.52), and conversely, the oil and oil products sector with low profit rate (M = -44.33) and low markup (M = 1.06). However, exceptions exist, such as the real estate sector, which despite a high markup (M = 3.26), exhibits a negative π rate (M = -12.30). This may suggest that despite strong market power, the sector faces profitability challenges, potentially due to factors like high operational costs, market fluctuations, or significant investments that do not immediately translate into profits.

Similarly, a positive relationship is generally observed between ROA and markup, with the financial services sector demonstrating high ROA (M = 18.49) and high markup (M = 2.52), and the oil and oil products sector exhibiting low ROA (M = 6.19) and low markup (M = 1.06). However, the gaming and recreation sector, with a moderate markup (M = 2.06), exhibits the lowest ROA (M = 2.39), indicating market power but inefficient asset utilisation. These countervailing examples underscore the fact that a high markup does not invariably translate into high profitability or efficient asset utilisation. Various factors, such as operational costs, market conditions and asset management practices, play crucial roles.

4.2 Markup Evolution

The aggregate markup for the period 2001 to 2019 shown in Figure 1 ranges from 1.42 to 2.03 in 2013 and 2005, respectively. The average for the 19-year period is 1.70. There is an upward trend from the beginning of the sample period until 2005. The global financial crisis, which commenced in 2007 and ended in 2009, is one of the

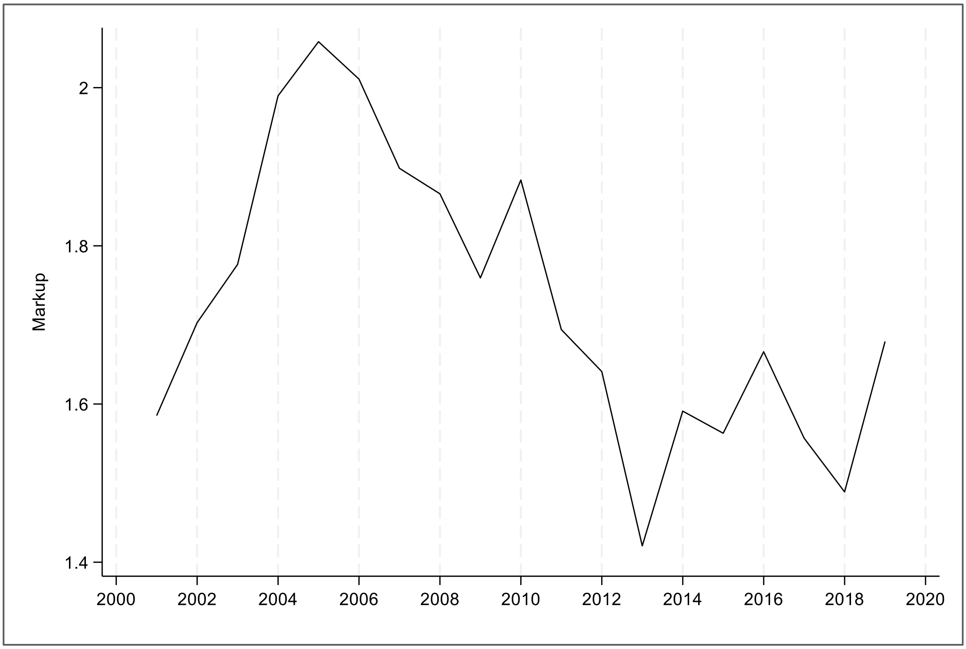

Figure 1. Sales-weighted aggregate markup

reasons for the succeeding downward slide. After a recovery in 2010, a precipitous decline that bottomed out in 2013 is seen. From this point on, a rising but relatively flat trend allowed the 2019 level to reach the 2011 level of 1.68. One can divide the entire period into two subperiods. The average markup from 2001 to 2010 is 1.79. From 2011 onward, the average markup is 1.58.

4.3 Markup Distribution

Breaking down the aggregate markup into various distributions can provide valuable insights that are not apparent from the aggregate result alone. It can highlight variations in data (by firm size and sector), as well as identify patterns and trends (by time and deciles).

(a) *Distribution by firm size*. Figure 2 shows the direct relationship between the markup and firm size, as measured by total asset holdings. The mean and median markup of the largest 20% of firms (quintile 5) are 2.29 and 1.601, respectively, while the lowest 20% of firms (quintile 1) has a mean and median of 1.71 and 1.23, respectively.

(b) *Distribution by sector*. Figure 3 shows the 19-year average markup, while Figure 4 depicts the markup movement of the 16 sectors. The real estate sector has the highest 19-year average markup of 3.26, followed by the technology sector at 3.09. The technology sector encompasses telecom firms, software companies and internet service providers. The transportation sector, meanwhile, has a 19-year average markup of 1.01.

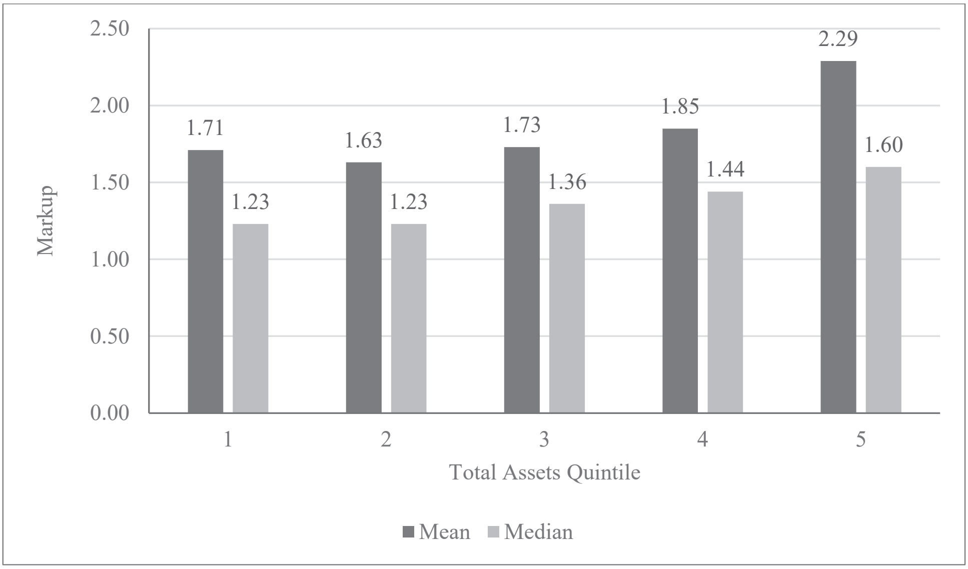

Figure 2. Average and median firm markup (by firm size)

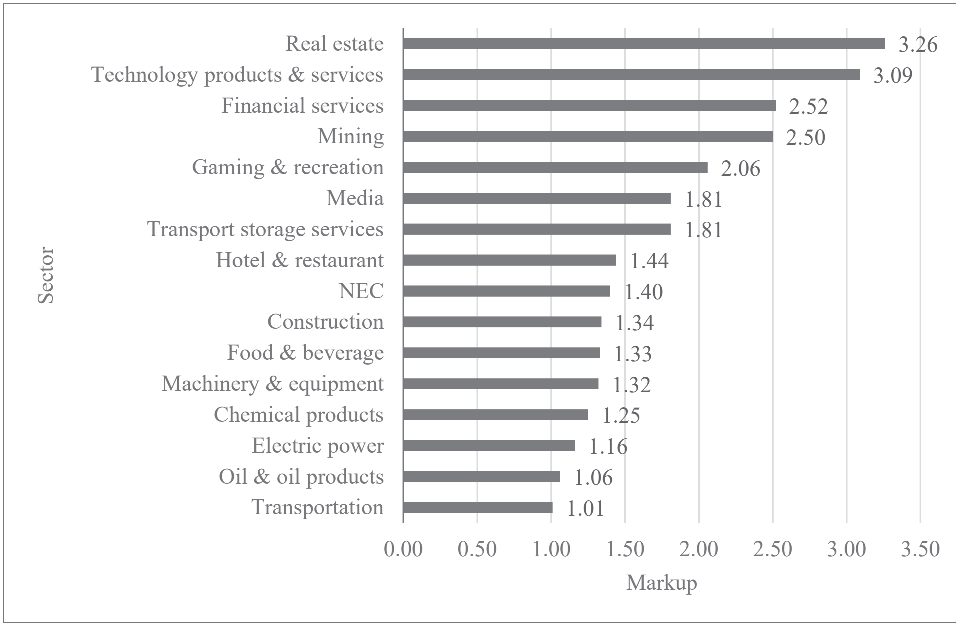

Figure 3. 19-year average sectoral markups, 2001 to 2019

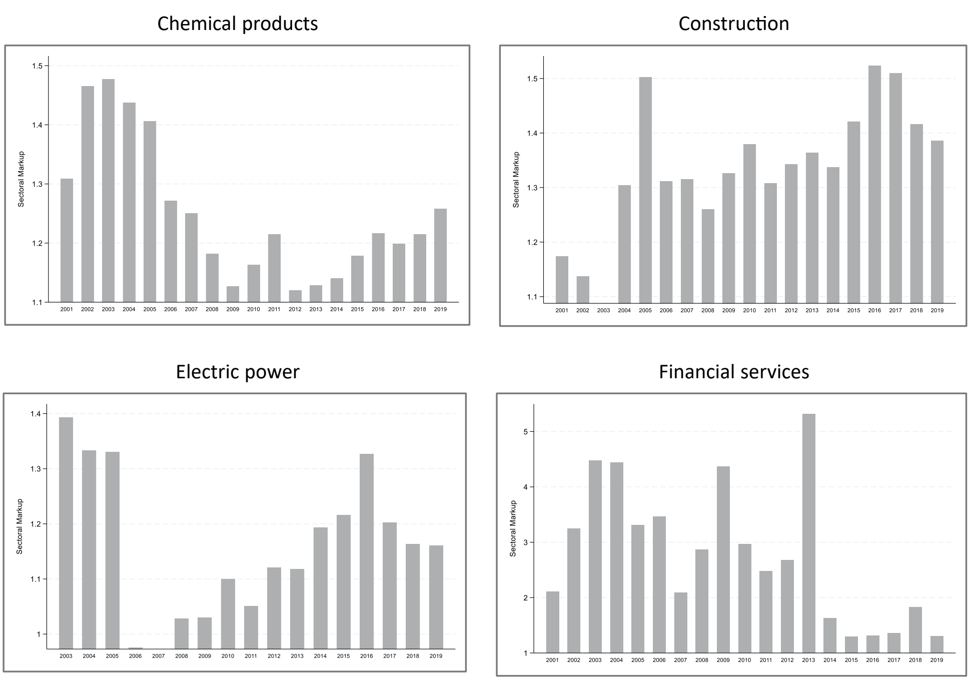

Figure 4. Sectoral markups, 2001 to 2019

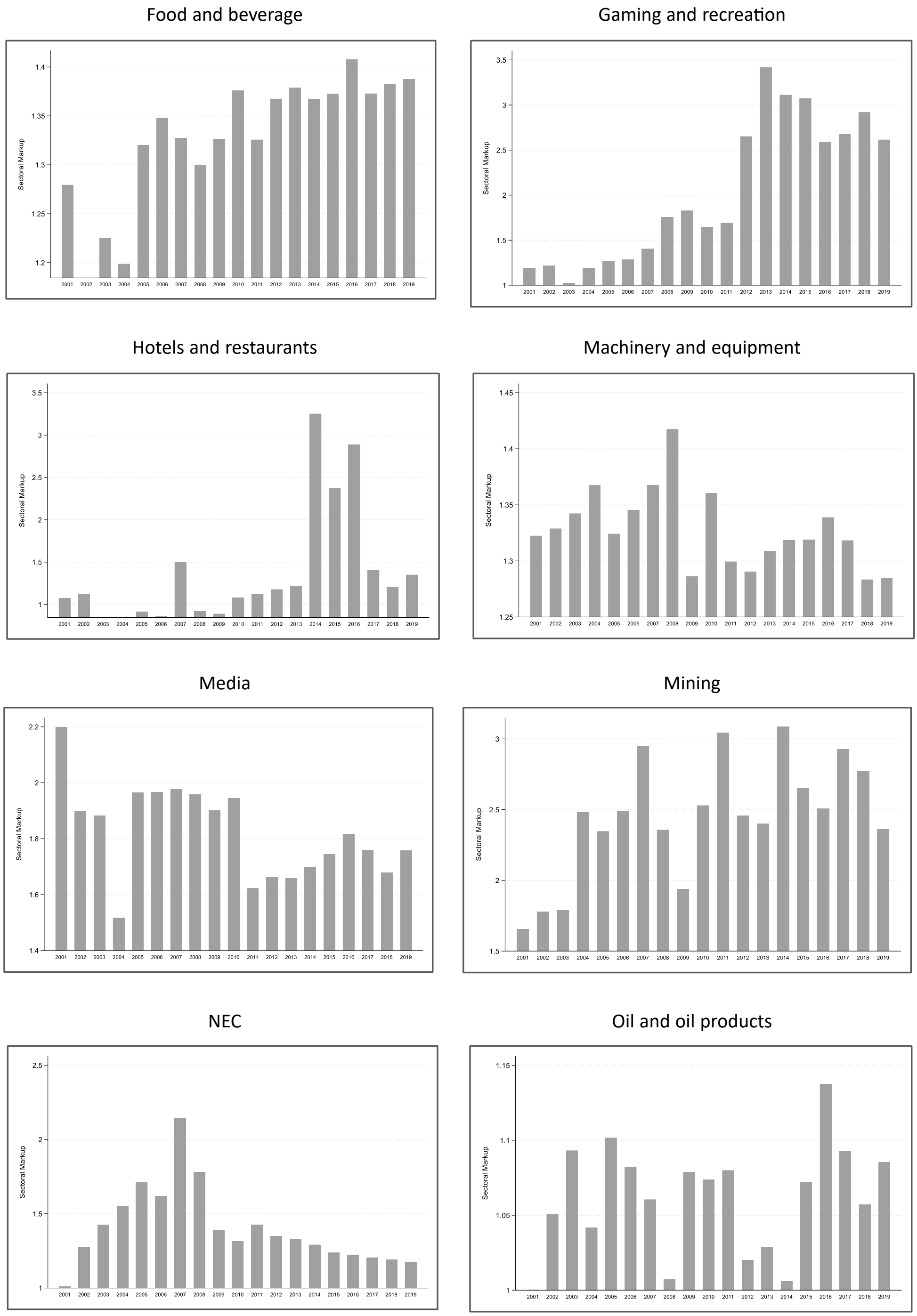

Figure 4. Continued

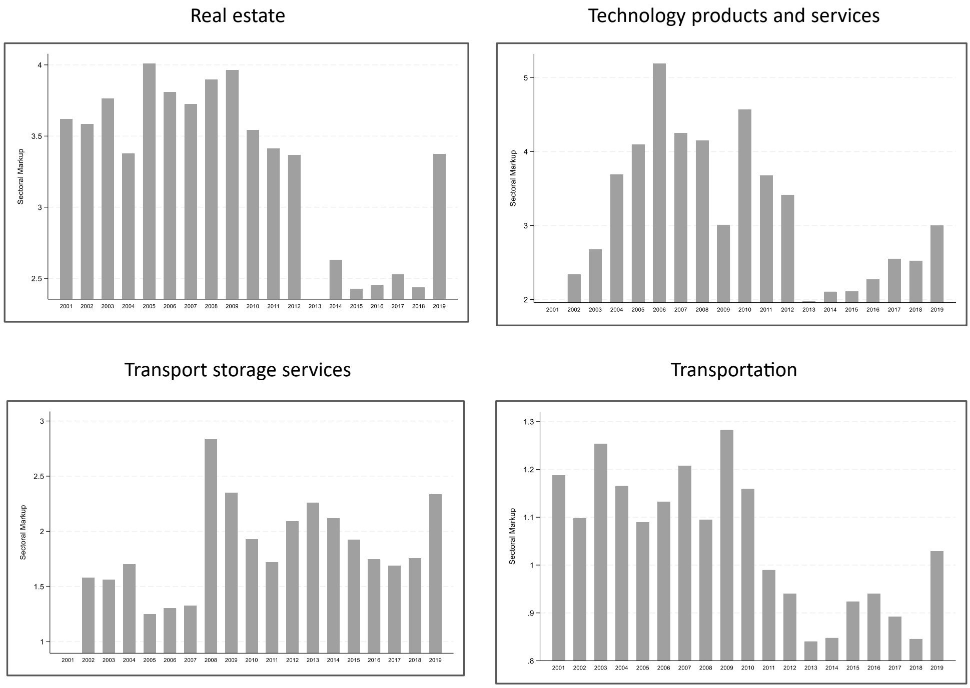

Figure 4. Continued

(c) *Distribution by time*. The nature and characteristics of firms driving the aggregate markup movement and influencing its evolution have garnered research attention (see De Loecker et al., 2020; Díez et al., 2018). Following De Loecker et al. (2020), Figure 5 maps the markup distribution at the beginning (2001) and end (2019) of

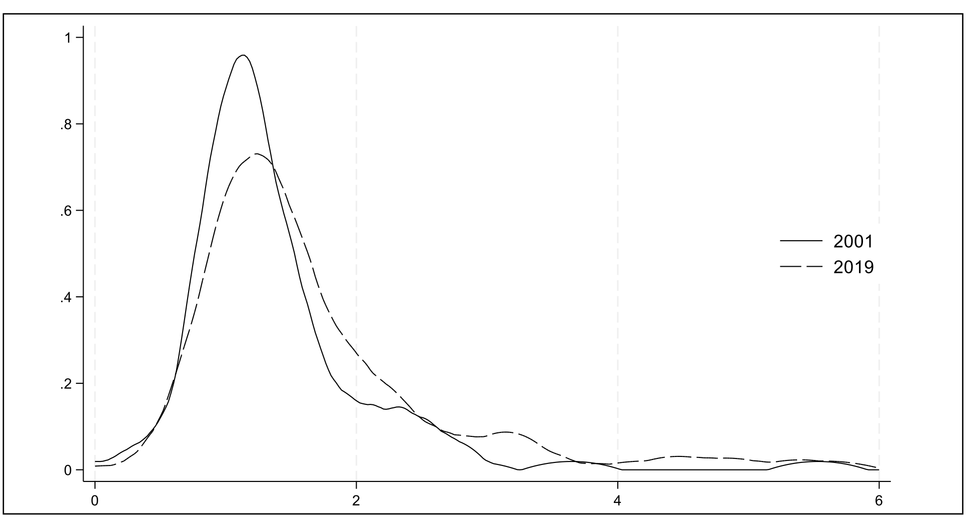

Figure 5. Kernel density estimates (unweighted markups)

the sample period. It is clear from the kernel density plot that the 2019 distribution is flatter and has a thicker upper tail, indicating an increase in high markup firms compared to the previous two decades.

(d) *Distribution by decile*. Using sales weights on the aggregate markup yields a clearer picture of the markup distribution. For comparability with the aggregate markup, firms are ranked based on percentiles derived from firm markups weighted by their market share over the entire sample period. Figure 6 graphically displays the calculated moments of the distribution. It reveals that the aggregate markup movement is largely driven by firms in the top decile of the markup distribution. This category also exhibits higher volatility than other decile groups. Conversely, the median remains stable, indicating markups in the lower half of the distribution experience minimal fluctuations in markups.

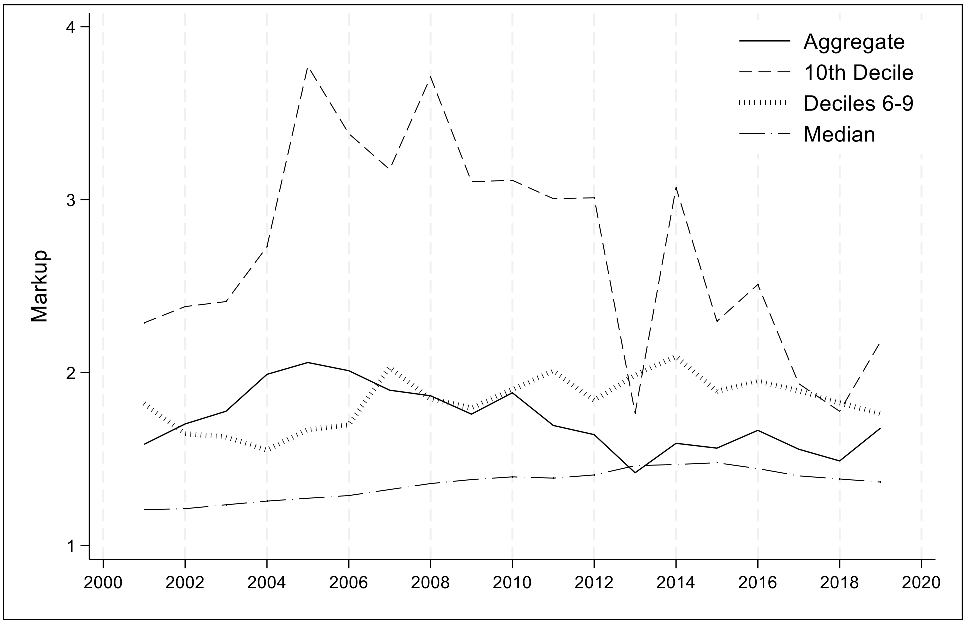

Figure 6. Markup distribution (sales weighted)

5. Estimation Results

This section explores the relationship between markups and other key variables. Regressions are conducted to assess the association between markups and firm performance indicators (i.e., π rate and ROA), as well as markups and macroeconomic indicators (i.e., interest rates and exchange rates).

5.1 Markup in Relation to Firm Performance

The markups derived in this study can also be compared with other profitability measures. This analysis focuses on whether firms set markups solely in response to changes in other market power measures or their components. If so, the firm's markup is a poor indicator of market power. The data sourced from Refinitiv Datastream/LSEG allows this study to calculate firm i's π, which can be compared with the markup calculations of this study. Economic profit can be written as:

$$\Pi_{it} = SALES_{it} - COGS_{it} - \mathrm{SGA}_{it} - r_{it}k_{it} \qquad (10)$$

where $SALES_{it}$ is total sales. $COGS_{it}$ is the cost of goods sold. SGA_{it} adds up all other expenses incurred but are not used directly to produce the goods (selling, general and administrative expenses.) This set of expenses mostly covers fixed costs, but a few may be classified as variable depending on the sector where the firm belongs. k_{it} is real physical capital; $r_{it} = p_t^k \bullet R_t - \hat{p}_t^k + \delta_t$ is the user cost of capital – δ_t is the exogenous depreciation rate of capital (set at 10%), $\hat{p}_t^k$ is the capital inflation rate, and R_t is the interest rate.

The π rate is defined as the ratio of π to total sales, $\pi_{it} = \Pi_{it}/SALES_{it}$:

$$\pi_{it} = 1 - \frac{COGS_{it}}{Sales_{it}} - \frac{SGA_{it}}{Sales_{it}} - \frac{r_{it}k_{it}}{Sales_{it}} = 1 - \frac{\theta_{it}}{\mu_{it}} - \frac{SGA_{it}}{Sales_{it}} - \frac{r_{it}k_{it}}{Sales_{it}} \qquad (11)$$

where $COGS_{it}/SALES_{it}$ is the variable input's share to total sales and is denoted by α_{it} in the previous section. It is apparent from the definition that there is a positive relation between the markup and the π rate, but this may not always be the case because of the presence of two other terms in Equation 11. For example, a firm can raise its markup in the presence of rising overhead costs (a component of SGA_{it}) to prevent π from falling or just to maintain a certain profit level. Or it can also raise markups simply to recover large, fixed capital costs.

The return on assets, $ROA_{it} = \Pi_{it}/Assets_{it}$, is another measure of profitability. This and the π rate are aggregated using sales weights and presented in Figure 7 along with the aggregate markup. ROA_{it} and π_{it}, both in percentage terms, are on the right scale, while the aggregate markup in gross rates is on the left scale. A generally positive pattern of relationship between the markup on the one hand and the π rate, and the *ROA* on the other hand, can be discerned from the figure.

Table 4 presents firm level fixed effects panel regressions of the π rate and ROA against the markup and market share. The market share is calculated as the share of the firm's sales to total sectoral sales. All the variables are in logarithms. It is easily seen that the markup coefficient is significantly different from zero but is not significantly different from 1. This shows a unit elastic relationship between the π rate and ROA, on the one hand versus the markup.

[5] Estimating the user cost of capital is inherently difficult owing to data constraints. For this study, it is assumed to be the same for all firms but varies per period. R_t is the inflation adjusted interest rates on government securities, and p_t^k is the implicit price index for gross domestic capital formation (GDCF) in the national accounts. Capital is the firm's PPEG series found in Refinitiv Datastream/LSEG and is adjusted using the GDCF deflator.

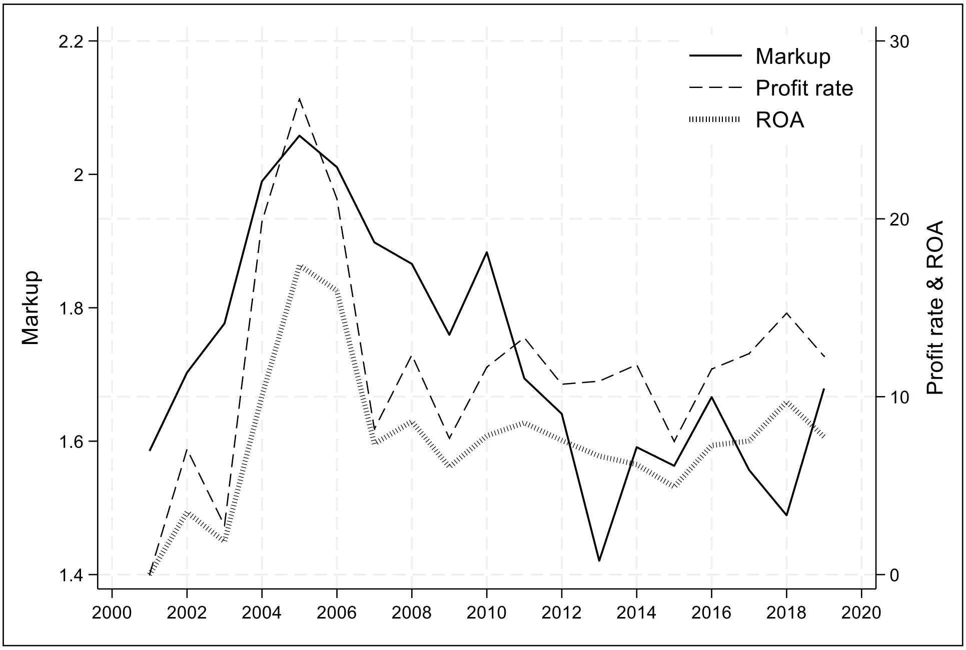

Figure 7. Profitability measures

Table 4. Regression results

	π Rate[1]	π Rate[1]	π Rate[1]	ROA[2]	ROA[2]	ROA[2]
Markup[3]	0.991*** (0.172)	1.018*** (0.170)	0.960*** (0.161)	0.918*** (0.174)	0.962*** (0.171)	0.892*** (0.174)
Market share[4]		0.291*** (0.059)	0.233*** (0.063)		0.470*** (0.109)	0.387*** (0.112)
Time Effects	Yes	Yes	No	Yes	Yes	No
F-stat: Time Effects = 0	5.56	6.05		3.94	5.48	
(p-value)	(0.00)	(0.00)		(0.00)	(0.00)	
No. of observations	1,241	1,241	1,241	1,241	1,241	1,241
No. of firms[5]	157	157	157	157	157	157

Notes: Standard errors in parentheses; * p<0.10, ** p<0.05, *** p<0.01.
[1] Profit rate, see equation 11.
[2] Return on assets = Economic profit/Total assets.
[3] Markup, see equation 3.
[4] Market share = Firm sales/Sectoral sales.
[5] Fewer than 212 non-financial PLCs final study sample size due to missing data required for the estimation of the regression models.

5.2 Markup in Relation to Macroeconomic Environment

The aggregate markup derived from microeconomic estimates can be related to some selected macroeconomic variables. Graphical representations of the relationship of the aggregate markup with interest rates and exchange rates in Figures 8 and 9, respectively, appear to show a general co-movement of the aggregate markup and these macro variables.

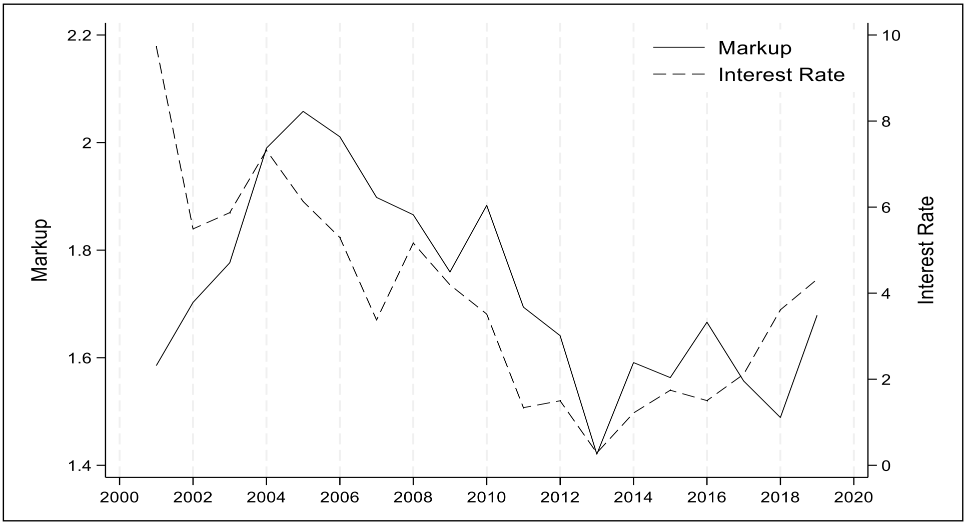

Figure 8. Markup and interest rates

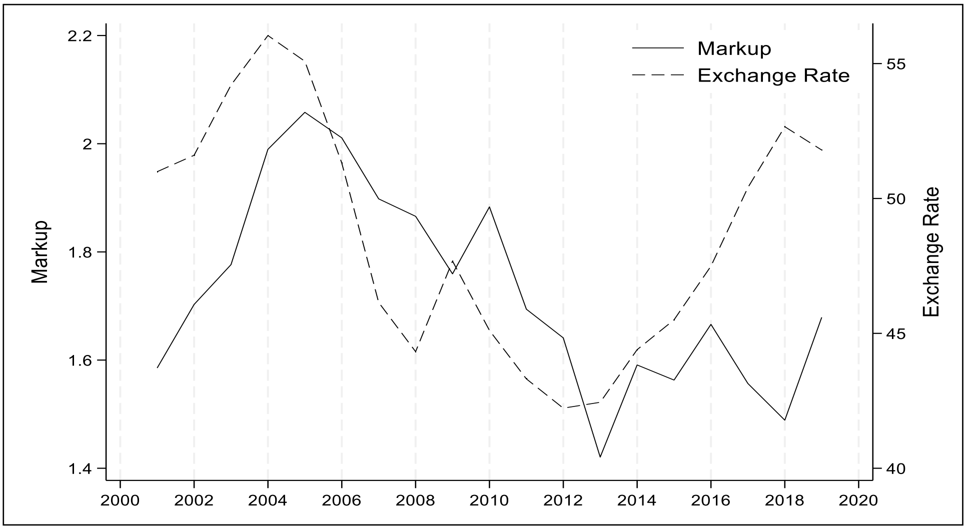

Figure 9. Markup and exchange rates

Table 5. Regression results – Dependent variable: firm markup

Assets	0.095***	0.080**	0.089***
	(0.03)	(0.03)	(0.03)
Interest rates		-0.058***	
		(0.02)	
Exchange rates			-0.639***
			(0.19)
Constant	-43.875	-25.457	207.951***
	(29.75)	(28.60)	(68.57)
No. of observations	2662	2662	2662
No. of firms[1]	195	195	195

Notes: Standard errors in parentheses; * p<0.10, ** p<0.05, ***p<0.01.
[1] Fewer than 212 non-financial PLCs final study sample size is due to missing data required for the estimation of the regression models.

Probing deeper into the relationship, fixed effects panel regressions in Table 5 show statistically significant effects of the macro variables on firm level markup movements. All variables are in logarithms. The total assets variable is an explanatory variable accounting for firm size, and the exchange rates and interest rates are used separately as control variables.

It is clear that the aggregate markup movements in the Philippines do not follow the global trend of rising markups reported by Díez et al. (2021). Based on Figures 8 and 9, the Philippine aggregate markup movement appears to be influenced by macroeconomic events. However, causation can go in the opposite direction, which means macro variables should be endogenously determined. This, however, requires a broader macroeconomic modelling framework, and is another area for further study.

6. Conclusion

This study estimates markups of non-financial public firms using annual financial statement data from 2001 to 2019 to analyse trends in market power in the Philippines, a modestly sized and growing EMDE. Unlike results of prior studies focused on AEs, the Philippines weighted average of firm markups does not show a consistently rising aggregate markup trend. Furthermore, the Philippines' aggregate markup movement appears to be influenced by macroeconomic events.

Like the findings of prior studies focused on AE, the Philippines' markup distribution generally rises with the size of the firm. The markup trend movement is also largely driven by firms at the top decile of the markup distribution. Lastly, unsurprisingly, different sectors have different markup trends, given their different industry and competitive structures.

Additionally, at the microeconomic level, this study demonstrates that firm level markups serve as valuable indicators of market power and degree of competition within an industry. This knowledge allows policymakers to focus their attention on specific sectors, enabling the implementation of targeted interventions, such as trade and industrial policies, competition policies and antitrust regulations, to foster a more competitive landscape. At the macroeconomic level, this study highlights that markups reflect the economy's response to aggregate demand shocks, influencing firms' pricing and output decisions. Consequently, policymakers should consider the economy's market structures when formulating macroeconomic policies, including decisions on interest rates and money supply. By understanding the dynamics of markups, policymakers can better anticipate the effects of macroeconomic policies on inflation, employment and overall economic stability, ensuring that interventions are both effective and equitable.

This study, while providing valuable insights for policymakers, is subject to certain limitations, such as the data and sample period. These limitations, however, also suggest promising avenues for future research. Firstly, the analysis is restricted to Philippine PLCs, which, while representing a significant portion of the economy, do not encompass the entire spectrum of firms. Expanding the analysis to include privately held companies, as suggested by Calligaris et al. (2018), would provide a more comprehensive picture of market power dynamics in the country. Secondly, this study relies on aggregated accounting data, which may not fully capture the nuances of firm level behaviour. Thirdly, the sample period is limited to the pre-COVID-19 era. Extending the analysis to include the COVID-19 period and beyond would allow for an investigation of the potential impact of the pandemic on input-output relationships and firm level markups.

Furthermore, this study primarily focuses on broad trends in aggregate markups. Future research could delve deeper into specific industries, e.g., investigating the effects of product differentiation in the real estate sector, studying regulation and fixed costs in the transportation sector. By examining sectoral-level dynamics, including sector-specific developments, mergers and acquisitions, entry and exit of firms, and behaviour of dominant firms, researchers can explain large markup differences between sectors or the homogeneity and heterogeneity of markups within sectors (Tamminen & Chang, 2013). Additionally, while it explores the influence of macroeconomic variables on markups, it acknowledges the potential for reverse causality. A more comprehensive framework that endogenises macroeconomic variables is necessary to fully understand this intricate relationship. Finally, it could be further extended to explore the broader macroeconomic implications of markups, including their impact on labour and capital shares, labour market outcomes, income inequality, productivity growth, innovation, investment rate, firm entry and exit, and competition policy, as highlighted by De Loecker et al. (2020) and Syverson (2019).

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