

BOTTOM-UP MARKUP FLUCTUATIONS*

ARIEL T. BURSTEIN
VASCO M. CARVALHO
BASILE GRASSI

We study markup cyclicalities in a granular macroeconomic model with oligopolistic competition. We first characterize how firm, sectoral, and aggregate markups comove with output at different levels of aggregation in response to firm-level shocks. We quantify the model's ability to reproduce salient features of the cyclical properties of measured markups in French administrative firm-level data from the bottom (firm) level to the aggregate level. We document that (i) firm-level markups rise with market share and sector-level markups with concentration, (ii) the relationship between markups and sectoral output varies by firm size—negative for small firms but positive for large ones, (iii) sector-level markups move positively with sectoral output, and (iv) sectoral markups show no systematic relationship with aggregate output. Our model helps rationalize these seemingly conflicting patterns of markup cyclicalities in the data. *JEL codes:* D21, D22, D43, E32.

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I. INTRODUCTION

A long tradition in the business cycle literature evaluates models by how well they match salient data moments, such as the relative volatility and correlation with GDP of key macroeconomic aggregates. Although there is broad consensus concerning, for example, the behavior of consumption, investment, or unemployment over the business cycle, disagreement lingers, both in terms of theory and measurement, over the cyclical behaviour of markups (see [Nekarda and Ramey 2013, 2020](#); [Bils, Klenow, and Malin 2018](#)).¹

In this article, we reexamine this question by studying the cyclical properties of markups at the firm, sector, and aggregate level, both theoretically and empirically, based on French administrative data. We consider a model of oligopolistic competition in which granular firm-level shocks result not only in sector- and economy-wide output changes, as in [Gabaix \(2011\)](#), but also in markup dynamics. We characterize the model's implications for comovement between output and markups, that is, “markup cyclicity,” at various levels of disaggregation from the bottom (firm) level up to the sector and aggregate levels and show how this comovement is mediated by market structure within and across sectors. We assess the ability of our granular oligopolistic setting to reproduce salient measures of the cyclical properties of markups in the French data at the firm, sector, and aggregate levels.

To model in a tractable way the determination and aggregation of markups in an economy featuring a large but finite number of sectors with a discrete number of firms, we use a nested constant elasticity of substitution (CES) demand structure studied in [Atkeson and Burstein \(2008\)](#).² Firms compete under flexible

1. Other studies contributing to the active debate on the sign and magnitude of markup cyclicity include [Bils \(1987\)](#), [Hall \(1988\)](#), [Anderson, Rebelo, and Wong \(2023\)](#), and [Stroebe and Vavra \(2019\)](#). In addition, a growing literature documents lower-frequency trends in markups, such as [De Loecker, Eeckhout, and Unger \(2020\)](#) and [De Loecker and Eeckhout \(2018\)](#).

2. A similar framework has been used in a number of macro applications to quantify the welfare costs of market power ([Berger, Herkenhoff, and Mongey 2022](#); [Edmond, Midrigan, and Xu 2023](#)), trends in market power ([De Loecker, Eeckhout, and Mongey 2021](#)), optimal product market policy ([Boar and Midrigan forthcoming](#)), managerial compensation ([Bao, De Loecker, and Eeckhout 2022](#)), wage inequality ([Deb et al. 2024](#)), pro-competitive gains from trade ([Edmond, Midrigan, and Xu 2015](#)), exchange rate pass-through ([Amiti, Itskhoki, and Konings 2019](#)), and granularity in trade ([Gaubert and Itskhoki 2021](#)). Other

prices, setting markups that are increasing in within-sector sales shares.³ Firm-level shocks follow a random growth process that generates empirically plausible firm dynamics, firm-size distributions, and granular sectoral and aggregate fluctuations (Carvalho and Grassi 2019). The model yields predictions for the joint behavior of within-sector market shares, markups, and output after exogenous changes in firm-level shifters. Furthermore, the model's convenient equilibrium aggregation yields simple sectoral and aggregate counterparts to many of these firm-level objects.

Our first theoretical contribution is to provide simple analytic expressions showing how the sign of markup cyclicity depends on the level of aggregation, the market structure in and across sectors, and the set of shocked firms.⁴ We show that sectoral output and markups comove positively in response to shocks to large firms in the sector, whereas they comove negatively in response to shocks to small firms. In turn, the effect of such shocks on the aggregate markup depends on the distribution of sector-level markups and sectoral expenditure shares. Under the additional assumption that shocks are uncorrelated across firms, we provide sufficient conditions for a positive asymptotic correlation between markups and output at the sectoral and aggregate levels.

Second, we compare theoretically the implications of our model to an alternative specification in which firm-level markups are heterogeneous but constant in response to shocks (i.e., com-

prominent work featuring fluctuations in market power in macroeconomic models include Galí (1994), Kimball (1995), Jaimovich and Floetotto (2008), and Bilbiie, Ghironi, and Melitz (2012).

3. Much of the literature on markup cyclicity is motivated by the implications of models with nominal rigidities (Rotemberg and Woodford 1999 for a comprehensive early survey), which depend on the nature of nominal rigidities (prices versus wages) and on the source of aggregate shocks (e.g., monetary versus productivity). By contrast, we examine how far a model with flexible prices and granular firm-level shocks can go in accounting for observed patterns of markup cyclicity at different levels of disaggregation. See Mongey (2021) and Wang and Werning (2022) for recent analyses of money nonneutrality in an oligopolistic model like ours with price rigidities.

4. Grassi (2018) studies the role of input-output linkages and endogenous markups in shaping comovement of sector-level variables, providing an analytical characterization of the effect of microeconomic shocks on aggregate output using an approximation with respect to the deep parameters of the model. Our analytic results make use of a different approximation with respect to firm-level idiosyncratic shocks, similar to the one used in, for example, Gopinath, Itskhoki, and Rigobon (2010), Burstein and Gopinath (2014), and Amiti, Itskhoki, and Konings (2019) in the context of exchange rate shocks.

plete pass-through) so that sectoral and aggregate markups only change due to between-firm reallocation and not within-firm markup changes. We show that although within-firm markup changes account for half of sectoral markup fluctuations in the variable-markup model, changes in sectoral and aggregate markups can be larger or smaller than in the constant-markup model, depending on parameter values, because the extent of between-firm reallocation falls with incomplete pass-through. In addition, we provide asymptotic formulas for sectoral and aggregate output volatility, which generalize those in [Gabaix \(2011\)](#) to an oligopolistic setting with variable markups. We show how introducing variable markups dampens granular aggregate volatility, acting in a similar way to a decline in the Herfindahl index. Intuitively, when pass-through rates are lower for larger firms, the weight of large-firm shocks in the price index is effectively reduced.

Our empirical analysis and calibration of the model is based on French administrative firm-level annual data over 26 years (1994–2019) covering approximately 400,000 firms a year. We compute empirical distributions of firm market shares, sectoral concentration, and output over time. To obtain a measure of firm-level markups, which we aggregate at the sector- and economy-wide levels, we follow the methodology in [De Loecker and Warzynski \(2012\)](#), [De Loecker et al. \(2016\)](#), and [De Ridder, Grassi, and Morzenti \(2024\)](#).⁵ This approach requires output elasticities for some flexible input, which we obtain by estimating production functions at the two-digit sector level for a subset of firms and years where quantity information—rather than revenues only—is available and then applying these estimates to the full sample of firms. By using firm-level quantities instead of revenues, our markup measures circumvent some of the biases discussed in [Bond et al. \(2021\)](#) and [De Ridder, Grassi, and Morzenti \(2024\)](#). We use our measure of markups to calculate several metrics of markup cyclicalities that we compare with model-generated data over short (25-year) samples.

5. Given the level of aggregation in our baseline data set, we do not measure markups at the level of geographic regions, as in [Anderson, Rebelo, and Wong \(2023\)](#), or products, as in [De Loecker et al. \(2016\)](#). For consideration of pricing with multiproduct firms in a similar framework to ours, see [Hottman, Redding, and Weinstein \(2016\)](#).

We start by analyzing a basic mechanism in our oligopolistic setting: in a narrowly defined sector, a firm's market power is increasing in its market share. This relationship implies a positive correlation between firm-level markup and firm-level market share, both in the cross section and over time. Moreover, aggregating firm-level outcomes implies the same correlation between sectoral markups and sectoral concentration. We find support for these predicted correlations in the French data at the firm and sector levels, in the cross section, and over time.⁶ Moreover, changes in firm-level markups account for a sizable portion of changes in sectoral markups both in our model (50%) and in the data (59% for the median sector).⁷

Second, we examine in the data and calibrated model three measures of markup cyclicity. We start by examining how firm-level markups covary with sector-level output. We find that markups are “countercyclical” for the average firm, but this relation switches sign for large firms. This is consistent with findings in [Hong \(2017\)](#) that markups are more countercyclical for small firms than for large firms. Our model reproduces this heterogeneity in markup cyclicity because the typical sectoral expansion is driven by shocks to large firms and these firms increase markups as their market share rises. Consistent with this, we show that market shares of large firms are procyclical with respect to sectoral output.

We proceed to evaluate notions of sector-level markup cyclicity. Following [Nekarda and Ramey \(2013\)](#) (the working paper version of [Nekarda and Ramey 2020](#)), we ask whether sector markups comove with sector output over the business cycle. Like [Nekarda and Ramey \(2013\)](#) for the United States, we find evidence for a positive systematic comovement between the two measures, or “procyclicality,” in the French data. The model simulations also reproduce this fact, as anticipated in our theoretical discussion. Also consistently with the model mechanism, we find

6. Relatedly, [Brooks, Kaboski, and Li \(2021\)](#) and [Dhyne, Kikkawa, and Magerman \(2022\)](#) provide evidence of a positive relation between market shares and markups in the time series using firm-level data from China and Belgium, respectively.

7. This is consistent with [Baqae and Farhi \(2020\)](#), Figure 3, showing that within-firm changes in markups in the United States are quantitatively important in accounting for high-frequency movements in aggregate markups.

that in the data, sectoral expansions tend to be associated with an increase in sectoral concentration.

Finally, we follow the work of [Bils, Klenow, and Malin \(2018\)](#), who investigate yet another notion of cyclicity: the extent to which sector-level markups comove with aggregate output. Although sectoral markups in our data display robust procyclical patterns in their own sectors, their relationship with aggregate output is less robust in terms of sign (ranging from acyclical to countercyclical) and significance. Simulations of our model imply that this comovement measure is not statistically different from zero.

Overall, we document seemingly conflicting patterns of markup cyclicity across different layers of aggregation despite using a single data set and measure of firm-level markups. Hence, by exploiting different reduced-form measures of markup cyclicity, two researchers may arrive at opposing conclusions even in a single data set. Our model can reproduce qualitatively and sometimes quantitatively these different reduced-form measures of markup cyclicity.

Finally, we examine the model's implications for fluctuations in aggregate markups and output. Our baseline calibration features only granular firm-level shocks and abstracts from aggregate shocks that leave the firm-size distribution unchanged because they do not affect markups. We use this quantitative laboratory featuring realistic heterogeneity in and across sectors to assess quantitatively the contribution of idiosyncratic shocks to aggregate output and markup fluctuations. Importantly, compared with prior work on the granular origin of business cycles (e.g., [Gabaix 2011](#); [Carvalho and Grassi 2019](#)), our model features movements in desired markups that can partly offset the effect of own firm-level shocks or magnify the effect from shocks to competing firms.⁸ Our quantitative model generates roughly 25%

8. [Gaubert and Itskhoki \(2021\)](#) study the granular origins of a country's comparative advantage in an oligopolistic framework that is similar to ours. For work on the granular origins of business cycle fluctuations—but featuring either perfect competition or constant markups—see [Carvalho and Gabaix \(2013\)](#) on the evolution of business cycle volatility over time and across countries and [di Giovanni and Levchenko \(2012\)](#) or [di Giovanni, Levchenko, and Mejean \(2018\)](#) for granular settings linking trade, aggregate volatility, and cross-country comovement. [Di Giovanni et al. \(2014\)](#) provide an empirical benchmark for the role of granularity in aggregate fluctuations. [Pasten, Schoenle, and Weber \(2020\)](#) examine aggregate granular fluctuations in a multisector model allowing for changes in

(on average, across 25-year simulated samples) of the volatility of aggregate output in the French data. To put this number in perspective, it is slightly lower than the 30% ratio reported in [Carvalho and Grassi \(2019\)](#) for a heterogeneous-firm model featuring granular but price-taking firms calibrated to U.S. data. Furthermore, our model additionally yields a ratio of markup volatility relative to output volatility of 0.36, close to the 0.40 ratio observed in data.

Turning to aggregate markup cyclicalities, our model implies a counterfactually large and positive point estimate for the correlation between aggregate output and markups relative to the data. However, there is substantial variation in point estimates across 25-year simulated samples. This is because, as our analytic expressions show, the extent of markup cyclicalities depends on the set of shocked firms, which vary across small samples. Moreover, superimposing aggregate productivity shocks to account for the overall aggregate volatility reduces this correlation significantly. Finally, the magnitude and cyclicalities of aggregate markups in our model is not very different to the case in which we counterfactually fix markups at their initial, heterogeneous equilibrium level. Of course, rather than exogenously fixing markups, our model provides a unified theory of both markup (level) heterogeneity across firms and endogenous markup changes.

The article is organized as follows. In [Section II](#), we present our granular oligopolistic setup and describe the equilibrium from the bottom (firm) level to the aggregate level. In [Section III](#), we characterize analytically various measures of markup cyclicalities at various aggregation levels. In [Section IV](#), we discuss the French administrative firm data, the markup estimation strategy, and the model calibration. In [Section V](#), we explore the relationship between markups and market shares in the model and data. In [Section VI](#), we compare a host of markup-cyclicalities metrics in the French data and model-generated data.

markups due to nominal price rigidities. Our emphasis on the micro origins of aggregate fluctuations is also related to the literature on production networks. See [Acemoglu et al. \(2012\)](#) for an initial benchmark, and [Grassi \(2018\)](#) for an analysis of how market power distorts the propagation of shocks along input linkages. [Baqae and Farhi \(2020\)](#) provide a very general characterization of the impact of microeconomic shocks on aggregate productivity and output in a large class of models in which productivities and wedges (e.g., markups) are exogenous primitives. [Baqae, Farhi, and Sangani \(2024\)](#) study the role of variable markups in shaping the aggregate implications of changes in market size.

In [Section VII](#), we examine fluctuations in aggregate markups and output implied by the model. [Section VIII](#) concludes. The [Online Appendix](#) contains proofs, details on markup estimation, additional results, and robustness checks.

II. MODEL

Our model consists of a representative household that supplies labor and consumes a fixed set of goods. These goods are produced by a discrete number of flexible-price firms that compete oligopolistically and are owned by the representative household. In this section, we describe the model and characterize the equilibrium, first within a sector and then at the aggregate level.

II.A. Preferences and Technologies

Households have intratemporal preferences at time t over consumption of a final composite good, Y_t , and labor, L_t , represented by the utility function

$$U(Y_t, L_t) = \frac{1}{1-\eta} Y_t^{1-\eta} - \frac{f_0}{1+f^{-1}} L_t^{1+f^{-1}},$$

where $f \geq 0$ is the Frisch elasticity of labor supply, and $\eta \leq 1$ is the constant relative risk aversion (which in our model shapes income effects in labor supply). Households choose consumption and labor to maximize utility subject to the constraint that consumption expenditures must not exceed the sum of wage payments and aggregate profits.

The final good aggregates output of N sectors according to a CES aggregator:

$$Y_t = \left[\sum_{k=1}^N A_k^{\frac{1}{\sigma}} Y_{kt}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}},$$

where Y_{kt} denotes sector k output, A_k is a demand shifter for sector k which we assume is constant over time, and $\sigma \geq 1$ is the elasticity of substitution across sectors.

Each sector k is itself a CES aggregator of the output of N_k individual firms given by

$$Y_{kt} = \left[\sum_{i=1}^{N_k} A_{kit}^{\frac{1}{\varepsilon}} Y_{kit}^{\frac{\varepsilon-1}{\varepsilon}} \right]^{\frac{\varepsilon}{\varepsilon-1}},$$

where Y_{kit} denotes the output of firm i in sector k , A_{kit} is a firm-quality shifter, and ε is the elasticity of substitution between the output of firms in sector k .⁹

We assume $\sigma \leq \varepsilon$, so goods are more substitutable within sectors than across sectors. With a finite number of sectors and a discrete number of firms per sector, firm-level shocks can generate aggregate fluctuations, as in [Gabaix \(2011\)](#). By contrast, with a continuum of sectors, as in [Atkeson and Burstein \(2008\)](#), firm-level shocks would not generate aggregate fluctuations.

Firm i in sector k produces output according to the constant returns to scale technology:

$$(1) \quad Y_{kit} = Z_{kit} L_{kit},$$

where Z_{kit} denotes the productivity of firm i in sector k and L_{kit} is a variable input, employment, that is perfectly mobile across firms.¹⁰ Labor market clearing requires that the sum of employment across all firms equals aggregate labor, L_t .¹¹ We assume that the number of firms per sector, N_k , is exogenously given.¹²

9. The model's implications for markups, market shares, and concentration measures are unchanged if A_{kit} is a taste shock. However, measures of aggregate output calculated using chain-weighted deflators are path-dependent in the presence of taste shocks (i.e., growth between t and t' depends on the sequence of shocks between t and t'); see [Baqaee and Burstein \(2023\)](#). For this reason, we abstract from taste shocks.

10. In [Online Appendix A.7](#) we provide analytic results allowing for decreasing returns to scale at the firm level.

11. Our results in [Section III](#) on firm-level and sectoral-level outcomes are unchanged if the variable input, L_{kit} , is a composite of multiple inputs (e.g., labor, intermediate goods, and capital) that is common across firms in the sector. The specific assumptions on the composition of this variable input matter only for the aggregate response of the economy to given firm-level shocks. When estimating markups in [Section IV](#), we assume the input L_{kit} is a translog combination of labor, capital, materials, and services inputs with parameters that vary by sector. We then compare measures of cyclicalities of estimated markups in the data with measures of cyclicalities implied by our model in [Section VI](#).

12. Endogenizing the number of firms per sector via a free-entry condition is computationally challenging in our model with oligopolistic competition, granular firm-level shocks, and realistic sectoral heterogeneity, requiring auxiliary assumptions to select among multiple equilibria with different sets of entering firms (see [Berry 1992](#); [Atkeson and Burstein 2008](#)). However, if entering and exiting firms have low market shares, changes over time in the number of firms would have small effects on sectoral and aggregate markups. Whereas in our data the number of firms changes year to year, in [Online Appendix D](#) we show robustness of our main empirical results to restricting the sample each period to continuing firms.

We introduce assumptions about the stochastic process of firm-level shocks A_{kit} and Z_{kit} in [Section III](#) for our asymptotic results and [Section IV](#) for our calibration strategy.

II.B. Market Structure and Sector Equilibrium

Here we describe the equilibrium in a sector. Firm i in sector k setting a non-quality adjusted price P_{kit} faces demand $Y_{kit} = A_k A_{kit} (P_{kit})^{-\varepsilon} (P_{kt})^{\varepsilon-\sigma} P_t^\sigma Y_t$, where the sector k price is

$$(2) \quad P_{kt} = \left[\sum_{i=1}^{N_k} A_{kit} P_{kit}^{1-\varepsilon} \right]^{\frac{1}{1-\varepsilon}},$$

and the aggregate price is

$$P_t = \left[\sum_{k=1}^N A_k P_{kt}^{1-\sigma} \right]^{\frac{1}{1-\sigma}}.$$

The markup for firm i in sector k , which we characterize below, is defined as the ratio of price to marginal cost,

$$(3) \quad \mu_{kit} \equiv \frac{Z_{kit} P_{kit}}{W_t},$$

where W_t is the price of the variable input (i.e., the wage). This markup determines how the firm's revenues are split into labor payments and profits, such that

$$L_{kit} W_t = \mu_{kit}^{-1} P_{kit} Y_{kit}, \quad \text{and} \quad \Pi_{kit} = (1 - \mu_{kit}^{-1}) P_{kit} Y_{kit}.$$

The market share of firm i in sector k , $s_{kit} \equiv \frac{P_{kit} Y_{kit}}{P_{kt} Y_{kt}}$, can be expressed in terms of markups and firm shifters, which are defined as a composite of quality and productivity shifters, $V_{kit} \equiv A_{kit} Z_{kit}^{\varepsilon-1}$. Specifically,

$$(4) \quad s_{kit} = \frac{V_{kit} \mu_{kit}^{1-\varepsilon}}{\sum_{i'=1}^{N_k} V_{ki't} \mu_{ki't}^{1-\varepsilon}}.$$

One can consider two alternative market structures. Firms maximize profits by choosing price, taking other firms' prices as given (Bertrand competition), or by choosing quantity, taking other firms' quantities as given (Cournot competition). In both cases, firms take into account that they are non-atomistic in their sector, and hence their choices affect sectoral output and prices. We assume, however, that individual firms behave as if the sector

they produce in is atomistic in the aggregate economy (as in the case of a continuum of sectors).¹³

Under these assumptions, equilibrium markups and market shares in each sector k solve the nonlinear system of equations given by the market share [equation \(4\)](#) and

$$(5) \quad \mu_{kit} = \begin{cases} \frac{\varepsilon}{\varepsilon-1} \left[1 - \left(\frac{\varepsilon-1}{\sigma} \right) s_{kit} \right]^{-1} & \text{under Cournot,} \\ \frac{\varepsilon}{\varepsilon-1} \left[\frac{1 - \left(\frac{\varepsilon-\sigma}{\varepsilon} \right) s_{kit}}{1 - \left(\frac{\varepsilon-\sigma}{\varepsilon-1} \right) s_{kit}} \right] & \text{under Bertrand.} \end{cases}$$

Under both formulations, since $\varepsilon > \sigma$, markups are increasing in market shares,¹⁴ with $\lim_{s_{kit} \rightarrow 0} \mu_{kit} = \frac{\varepsilon}{\varepsilon-1}$ and $\lim_{s_{kit} \rightarrow 1} \mu_{kit} = \frac{\sigma}{\sigma-1}$. If $\varepsilon = \sigma$, markups are common across firms and constant over time as in the standard monopolistically competitive model. In our analytic and quantitative results, we focus on the case of Cournot competition. It generates more markup variation than Bertrand and is thus better able to match estimates of incomplete pass-through and the markup-size relationship. In [Online Appendix A](#), we provide analytic results under Bertrand.

Two remarks are in order about firm shifters. First, firm-level market shares and markups in sector k depend only on relative firm shifters across firms in this sector. This result implies that market shares and markups in sector k do not vary in response to proportional changes in shifters to all firms in sector k (including sectoral demand shifters A_k), shocks in other sectors, or changes in the aggregate wage. It follows that aggregate shocks to firms in all sectors generate fluctuations in aggregate output but not in aggregate markups. For this reason, in our baseline quantita-

13. In [Online Appendix A.8](#) we solve for markups in the case in which each firm maximizes real profits internalizing the effect of their individual choice of output or prices on aggregate output and the real wage, thus relaxing our baseline behavioral assumption. Firms do not internalize the effect that changes in profits have on the welfare of the firm's owner ([Azar and Vives 2021](#)). We show that markups depend not only on the firm's sectoral sales share but also on the firm's sectoral employment share and the firm's economy-wide share in sales and employment, which increases the computational burden of solving the model. Applying the new formula using the sales and employment shares in our baseline calibration results has a negligible effect on markup levels compared to our baseline. This is because most sectors in our data are quite small.

14. The property is satisfied in a variety of models with variable elasticity of demand (see the reviews in [Burstein and Gopinath 2014](#) and [Arkolakis and Morlacco 2017](#)).

tive analysis we abstract from standard aggregate productivity shocks.

Second, the split of firm shifters into quality and productivity does not matter for the model implications on markups, concentration, and output (for the latter, this is as long as deflators use quality-adjusted prices) at the firm, sector, or aggregate levels. In practice, price deflators used by statistical agencies typically do not incorporate high-frequency changes in quality. Therefore, to compare output in the model and data, we only consider firm-level productivity shocks and abstract from quality shocks.

II.C. Sectoral Outcomes

We now describe how the model aggregates outcomes from the firm level to the sector level. We define the sectoral markup as the ratio of sectoral revenues to labor payments,

$$(6) \quad \mu_{kt} \equiv \frac{P_{kt} Y_{kt}}{W_t L_{kt}},$$

where sectoral employment is $L_{kt} = \sum_{i=1}^{N_k} L_{kit}$. Sectoral markups can be expressed as a harmonic mean (weighted by market shares) of firm-level markups,

$$(7) \quad \mu_{kt} = \left[\sum_{i=1}^{N_k} \mu_{kit}^{-1} s_{kit} \right]^{-1}.$$

Substituting the markup–market share relationship (equation (5)) under Cournot competition, we can express the sectoral markup, μ_{kt} , as a simple function of the sector's Herfindahl-Hirschman index, $HHI_{kt} = \sum_{i=1}^{N_k} s_{kit}^2$.¹⁵

$$(8) \quad \mu_{kt} = \frac{\varepsilon}{\varepsilon - 1} \left[1 - \left(\frac{\varepsilon}{\sigma} - 1 \right) HHI_{kt} \right]^{-1}.$$

Note the positive relationship between sectoral markup and HHI takes the same form as the firm-level relationship between markup and market share in equation (5). In the same way that a firm with a large market share charges a higher markup, a sec-

15. The HHI is an average of market shares, weighted by market shares themselves, and ranges between zero and one.

tor with a large average market share, that is, a high HHI, has a high sectoral markup as long as $\varepsilon > \sigma$.¹⁶

Sectoral markups can be expressed as the standard ratio between sectoral price and marginal cost (i.e., the ratio of wage to sectoral productivity), $\mu_{kt} = \frac{P_{kt}Z_{kt}}{W_t}$. Sectoral productivity, $Z_{kt} \equiv \frac{Y_{kt}}{L_{kt}}$, can be expressed in terms of firm-level markups and firm shifters as

$$(9) \quad Z_{kt} = \frac{\left(\sum_{i=1}^{N_k} V_{kit} \mu_{kit}^{1-\varepsilon} \right)^{\frac{\varepsilon}{\varepsilon-1}}}{\sum_{i=1}^{N_k} V_{kit} \mu_{kit}^{-\varepsilon}}.$$

II.D. Aggregate Outcomes

We describe how the model aggregates outcomes from the sector level to the aggregate level. We define the aggregate markup as the ratio of aggregate revenues and labor payments,

$$(10) \quad \mu_t \equiv \frac{P_t Y_t}{W_t L_t} = \left[\sum_{k=1}^N s_{kt} \mu_{kt}^{-1} \right]^{-1}.$$

As indicated by the second equality, aggregate markups can be expressed as a harmonic weighted average of sectoral markups, where sectoral expenditure shares are determined by sectoral markups and sectoral shifters $V_{kt} \equiv A_k Z_{kt}^{\sigma-1}$,

$$(11) \quad s_{kt} \equiv \frac{P_{kt} Y_{kt}}{P_t Y_t} = \frac{V_{kt} (\mu_{kt})^{1-\sigma}}{\sum_{k'} V_{k't} (\mu_{k't})^{1-\sigma}}.$$

Alternatively, under Cournot we can express the aggregate markup as a simple function of average sectoral HHI (weighted by sectoral expenditure shares) that mirrors the expressions for firm-level and sector-level markups in [equations \(5\) and \(8\)](#), respectively:

$$\mu_t = \frac{\varepsilon}{\varepsilon-1} \left[1 - \left(\frac{\varepsilon}{\sigma-1} \right) \sum_{k=1}^N s_{kt} HHI_{kt} \right]^{-1}.$$

The weighted average of sectoral HHIs is equal to the average market share across firms weighted by firms' expenditure share

16. A similar mapping between sectoral markups and concentration indices can be obtained under Bertrand competition (see [Grassi 2018](#)).

in the whole economy.¹⁷ When this weighted-average economy-wide market share is high, the aggregate markup is high.

Aggregate markups can also be expressed as the standard ratio between aggregate price and aggregate marginal cost, $\mu_t = \frac{P_t Z_t}{W_t}$, where aggregate productivity, $Z_t \equiv \frac{Y_t}{L_t}$, can be expressed in terms of sectoral markups and sectoral shifters as

$$(12) \quad Z_t = \frac{\left(\sum_{k=1}^N V_{kt} \mu_{kt}^{1-\sigma} \right)^{\frac{\sigma}{\sigma-1}}}{\left(\sum_{k=1}^N V_{kt} \mu_{kt}^{-\sigma} \right)}.$$

Finally, aggregate output and labor are given by

$$(13) \quad Y_t^{\eta+\frac{1}{\bar{\gamma}}} = \frac{Z_t^{1+\frac{1}{\bar{\gamma}}}}{f_0 \mu_t} \quad \text{and} \quad L_t = \frac{Y_t}{Z_t} = \frac{Z_t^{\frac{1-\eta}{\eta+\frac{1}{\bar{\gamma}}}}}{(f_0 \mu_t)^{\frac{1}{\eta+\frac{1}{\bar{\gamma}}}}}.$$

The aggregate markup μ_t distorts the leisure/consumption choice relative to the optimal allocation.

II.E. Summary of Equilibrium

Our model aggregates outcomes in a very parsimonious manner from the firm level to the sector level and from the sector level to the aggregate level. Here we summarize how to solve for prices and quantities as a function of time t of firm shifters, $\{V_{kit}\}$, and sectoral demand shifters, $\{A_k\}$.

Equilibrium firm-level markups and market shares, μ_{kit} and s_{kit} , are the solution to equations (4) and (5). Sectoral markups and productivities, μ_{kt} and Z_{kt} , are solved from equations (7) and (9), respectively, and sectoral expenditure shares, s_{kt} , from equation (11).

Aggregate markup, productivity, output, and employment, μ_t , Z_t , Y_t , and L_t , are solved from equations (10), (12), and (13). Setting $W_t = \bar{W}$ as the numeraire, sectoral and aggregate price levels, P_{kt} and P_t , are given by $P_{kt} = \frac{\mu_{kt} \bar{W}_t}{Z_{kt}}$ and $P_t = \frac{\mu_t \bar{W}_t}{Z_t}$. Sectoral output is solved from

$$Y_{kt} = A_k P_{kt}^{-\sigma} P_t^{\sigma} Y_t,$$

$$17. \quad \text{Specifically,} \quad \sum_{k=1}^N s_{kt} HHI_{kt} = \sum_{k=1}^N \sum_{i=1}^{N_k} s_{kt} s_{kit}^2 = \sum_{k=1}^N \sum_{i=1}^{N_k} \frac{P_{ki} Y_{ki}}{P_t Y_t} \frac{P_{kit} Y_{kit}}{P_{kt} Y_{kt}} s_{kit}.$$

and sectoral employment using $L_{kt} = \frac{Y_{kt}}{Z_{kt}}$. Firm-level expenditures and employment, $P_{kit}Y_{kit}$ and L_{kit} , are solved from $P_{kit}Y_{kit} = s_{kit}P_{kt}Y_{kt}$ and [equation \(6\)](#), respectively. Finally, given a split of firm shifters V_{kit} into productivity $\{Z_{kit}\}$ and quality $\{A_{kit}\}$, firm-level output Y_{kit} and price P_{kit} are solved from [equations \(1\) and \(3\)](#), respectively.

In the next section, we use a first-order approximation to characterize the equilibrium response to firm-level shocks at the firm, sectoral, and aggregate levels.

III. ANALYTIC RESULTS

Here we characterize, up to a first-order approximation, the equilibrium response of markups, prices, and output to firm-level shocks at the firm, sectoral, and aggregate levels.

First we introduce a first-order approximation to solve for changes in firm-level markups and market shares in a sector. We develop expressions for changes in prices, markups, and output in response to firm-level shocks, first at the sector level and then at the aggregate level. We provide expressions for asymptotic covariances between markup and output changes at different aggregation levels under the additional assumption that firm-level shocks are i.i.d. across firms and over time with variance $\sigma_v^2 \equiv \text{Var}[\hat{V}_{kit}]$. We focus on the case of Cournot competition and present results under Bertrand in the [Online Appendix](#). We highlight the role of variable markups versus constant markups in shaping markup cyclicity, as well as the effect of variable markups on aggregate output volatility.

III.A. Firm-Level Outcomes

Consider an initial equilibrium in sector k with market shares $\{s_{ki}\}$ and markups $\{\mu_{ki}\}$ where, for simplicity, we omit time subscripts in the initial equilibrium. Taking a first-order approximation of the expressions for market share ([equation \(4\)](#)) and firm-level markup ([equation \(5\)](#)), changes in the equilibrium market shares and markups are the solutions to the following linear system of equations

$$(14) \quad \begin{aligned} \hat{s}_{kit} &= \hat{V}_{kit} + (1 - \varepsilon) \hat{\mu}_{kit} \\ &- \sum_{i'=1}^{N_k} s_{ki'} \left(\hat{V}_{ki't} + (1 - \varepsilon) \Gamma_{ki'} \hat{s}_{ki't} \right), \end{aligned}$$

$$(15) \quad \widehat{\mu}_{kit} = \Gamma_{ki} \widehat{s}_{kit}.$$

Variables with hats denote log differences at time t relative to the initial equilibrium, for example, $\widehat{V}_{kit} \equiv \log V_{kit} - \log V_{ki}$, and Γ_{ki} denotes the markup elasticity with respect to market share for firm i in sector k evaluated at the initial equilibrium.

Markup elasticities under Cournot are, by [equation \(5\)](#),

$$\Gamma_{ki} \equiv \frac{\partial \log \mu_{ki}}{\partial \log s_{ki}} = \frac{\left(\frac{\varepsilon}{\sigma} - 1\right) s_{ki}}{\varepsilon - 1 - \left(\frac{\varepsilon}{\sigma} - 1\right) s_{ki}}.$$

As discussed, if $\varepsilon > \sigma$, markups are increasing in market shares. That is, $\Gamma_{ki} \geq 0$, with strict inequality if $s_{ki} > 0$. Moreover, markup elasticities are increasing in market shares. This property is satisfied in a variety of models of demand with variable elasticity, as discussed in [Burstein and Gopinath \(2014\)](#) and [Arkolakis and Morlacco \(2017\)](#).

Now we introduce pass-through elasticities, which are not required to solve for sectoral market shares and markups, but we use them in our analytic results that follow. Changes in firm-level prices are given by $\widehat{P}_{kit} = -\widehat{Z}_{kit} + \widehat{\mu}_{kit}$, where we used that the wage is the numeraire. Combined with [equations \(15\)](#) and $\widehat{s}_{kit} = \widehat{A}_{kit} + (1 - \varepsilon)(\widehat{P}_{kit} - \widehat{P}_{kt})$, we obtain

$$(16) \quad \widehat{P}_{kit} = \alpha_{ki} \left(-\widehat{Z}_{kit} + \Gamma_{ki} \widehat{A}_{kit} \right) + (1 - \alpha_{ki}) \widehat{P}_{kt},$$

where α_{ki} is the pass-through rate governing how firm-level prices respond to idiosyncratic shocks (given changes in sectoral price), given by

$$(17) \quad \alpha_{ki} = \frac{1}{1 + (\varepsilon - 1) \Gamma_{ki}}.$$

Conversely, $1 - \alpha_{ki}$ governs how prices respond to changes in sectoral price (given changes in marginal cost). Because markup elasticities are increasing in market shares (if $\varepsilon > \sigma$), pass-through rates are decreasing in market shares.¹⁸ To isolate the role of changes in markups in response to shocks, we consider an alternative case in which markups are fixed at the initial equilibrium levels, imposing $\Gamma_{ki} = 0$ and $\alpha_{ki} = 1$.

18. We can further solve for $\widehat{P}_{kit}$ using $\widehat{P}_{kt} = s_{ki} \widehat{P}_{kit} + (1 - s_{ki}) \widehat{P}_{k-it}$, where $\widehat{P}_{k-it}$ is the competitors' price index defined in [Amiti, Itskhoki, and Konings \(2019\)](#). We can rewrite [equation \(16\)](#) as $\widehat{P}_{kit} = \tilde{\alpha}_{ki} \left(-\widehat{Z}_{kit} + \Gamma_{ki} \widehat{A}_{kit} \right) + (1 - \tilde{\alpha}_{ki}) \widehat{P}_{k-it}$, where $\tilde{\alpha}_{ki} = \frac{\alpha_{ki}}{1 - (1 - \alpha_{ki}) s_{ki}}$, which is a U-shaped function of market shares s_{ki} .

III.B. Sectoral Outcomes

In this section, we characterize how sectoral prices, markups, and output respond to firm-level shocks and provide expressions for variances and covariances of markup and output changes over long realizations of shocks.

1. *Sectoral Prices.* As a first step in understanding changes in sectoral output, we solve for changes in sectoral prices (relative to the numeraire, i.e., the wage), which are related to sectoral output by CES demand, $Y_{kt} = A_k P_{kt}^{-\sigma} P_t^\sigma Y_t$.

Taking a first-order approximation of the sectoral price definition (equation (2)) and using firm-level price changes (equation (16)), log changes in sectoral prices can be expressed as a weighted average of firm shifters,

$$(18) \quad \hat{P}_{kt} = -\frac{1}{\varepsilon - 1} \frac{\sum_{i=1}^{N_k} s_{ki} \alpha_{ki} \hat{V}_{kit}}{\sum_{i=1}^{N_k} s_{ki} \alpha_{ki}},$$

where the weights are given by the product of market shares, s_{ki} , and pass-through rates, α_{ki} . Because $\varepsilon \geq 1$, sectoral prices fall in response to an increase in firm shifter.

To understand how sectoral price changes are shaped by pass-through rates, note that if $\alpha_{ki} = \alpha_k$, $\hat{P}_{kt}$ is independent of α_k for given market shares s_{ki} in the initial equilibrium. That is, the response in sectoral price is identical to that if markups are fixed at their initial level ($\alpha_{ki} = 1$). Intuitively, as pass-through α_k falls, the larger markup change by a firm to an own shock is exactly offset by a larger change in markup, in the opposite direction, of its competitors.

With heterogeneity in pass-through rates, because α_{ki} is decreasing in s_{ki} , there is a cutoff market share $\bar{s}_k^p$ such that a positive shock to firm i with $s_{ki} > \bar{s}_k^p$ results in a smaller reduction in sectoral prices than if markups are fixed at their initial level. Intuitively, firm i 's increase in markup more than offsets the markup decrease of its competitors. Conversely, a positive shock to firm i with $s_{ki} < \bar{s}_k^p$ results in a larger reduction in sectoral prices than if markups were fixed at their initial level.¹⁹

From equation (18), the asymptotic variance of price changes in sector k assuming that firm-level shifters are i.i.d. with com-

19. The threshold $\bar{s}_k^p$ is defined implicitly by $\alpha_k(\bar{s}_k^p) = \sum_{i=1}^{N_k} s_{ki} \alpha_{ki}$.

mon variance σ_v^2 is

$$(19) \quad \text{Var}[\hat{P}_{kt}] = \left(\frac{\sigma_v}{\varepsilon - 1} \right)^2 \sum_{i=1}^{N_k} \left(\frac{\alpha_{ki} s_{ki}}{\sum_{i'} \alpha_{ki'} s_{ki'}} \right)^2.$$

If markups are fixed at their initial level (or, more generally, if $\alpha_{ki} = \alpha_k$), this variance is proportional to the sectoral HHI, as in [Gabaix \(2011\)](#): $\text{Var}[\hat{P}_{kt}] = \left(\frac{\sigma_v}{\varepsilon - 1} \right)^2 \sum_{i=1}^{N_k} s_{ki}^2$. Comparing this expression with [equation \(19\)](#), we note $\text{Var}[\hat{P}_{kt}]$ is lower under variable markups than under constant markups if and only if the variance of $\frac{\alpha_{ki} s_{ki}}{\sum_{i'} \alpha_{ki'} s_{ki'}}$ is lower than the variance of s_{ki} . Because α_{ki} is decreasing in s_{ki} , this condition is satisfied if $s_{ki} \alpha_{ki}$ is increasing in s_{ki} (see condition A7 in [Online Appendix A.3](#)). Intuitively, under this condition, pass-through rates are lower for larger firms, effectively reducing the weight of large-firm shocks in the price index (with similar effects on volatility as a decline in the HHI).

2. Sectoral Markups. Changes in sectoral markups, defined in [equation \(7\)](#), can be decomposed into changes in markups within firms and the reallocation of expenditures between firms with heterogeneous markups:

$$(20) \quad \hat{\mu}_{kt} = \sum_{i=1}^{N_k} s_{ki} \frac{\mu_k}{\mu_{ki}} (\hat{\mu}_{kit} - \hat{s}_{kit}).$$

In [Online Appendix A.2](#), we derive the following expression for changes in sectoral markups:²⁰

$$(21) \quad \hat{\mu}_{kt} = 2 \left(\frac{1}{\sigma} - \frac{1}{\varepsilon} \right) \mu_k \sum_{i=1}^{N_k} s_{ki} \alpha_{ki} \left[s_{ki} - \frac{\sum_{i'} s_{ki'}^2 \alpha_{ki'}}{\sum_{i'} s_{ki'} \alpha_{ki'}} \right] \hat{V}_{kit}.$$

The following proposition states that a positive shock to firm i results in an increase in the sectoral markup if and only if firm i is sufficiently large in its sector.

PROPOSITION 1. Consider a positive shock to firm i in sector k , $\hat{V}_{kit} > 0$. Then, under Cournot competition, sector k markup increases, $\hat{\mu}_{kt} > 0$, if and only if $s_{ki} > \frac{\sum_{i'} s_{ki'}^2 \alpha_{ki'}}{\sum_{i'} s_{ki'} \alpha_{ki'}}$.

20. Ex ante firm heterogeneity is a necessary condition for sectoral markups to change in response to firm-level shocks. To see this, if s_{ki} and μ_{ki} are equal across all firms in sector k , [equations \(15\)](#), [\(20\)](#), and $\sum_{i=1}^{N_k} s_{ki} \hat{s}_{ki} = 0$ imply that $\hat{\mu}_{kt} = 0$.

Intuitively, recall from [equation \(20\)](#) that changes in sectoral markups reflect changes in firm-level markups (within term) and between-firm reallocation (between term). First consider the within term. A positive shock to firm i raises firm i 's markup and reduces it for competing firms. The former dominates if firm i is large, whereas the latter dominates if firm i is small. Now consider the between term. A positive shock to firm i reallocates market shares toward firm i , increasing the sectoral markup if firm i 's markup is sufficiently high (or equivalently, if its market share is sufficiently large). Therefore, the within and between terms push the sectoral markup in the same direction.

The “2” in front of [equation \(21\)](#) reflects the fact that the magnitude of the within term is equal to the magnitude of the between term (and hence each accounts for 50% of changes in sectoral markups). A change in parameters (e.g., an increase in $\varepsilon - \sigma$) that increases the sensitivity of markups to firm-level shocks (increasing the within term) also increases the dispersion of markups across firms (increasing the between term). In [Online Appendix A.1](#) we show that this 50–50 within/between decomposition of changes in sectoral markups under Cournot competition holds globally, not only up to a first order.

How do changes in sectoral markups compare in the specification with variable markups versus the specification with constant markups in which sectoral markups change only due to between-firm reallocation? If firm-level markups are fixed at their initial level (by imposing $\Gamma_{ki} = 0$ and $\alpha_{ki} = 1$), changes in sectoral markups in [equation \(20\)](#) are:

$$(22) \quad \hat{\mu}_{kt} = \sum_{i=1}^{N_k} s_{ki} \left(1 - \frac{\mu_k}{\mu_{ki}} \right) \hat{V}_{kit}.$$

In response to a positive shock to firm i , sectoral markups increase if and only if $\mu_{ki} > \mu_k$.

In general, we cannot easily compare [equations \(21\)](#) and [\(22\)](#). To make analytic progress, in [Online Appendix A.2](#) we restrict the extent of ex ante firm heterogeneity to two types and provide a simple sufficient condition for sectoral markups to change by more (and display a higher variance) under variable markups than under constant markups. Intuitively, changes in sectoral markups can be smaller under variable markups than under constant markups because the larger response of sectoral markups due to changes in firm-level markups is more than offset by a

smaller extent of between-firm reallocation from incomplete pass-through.

To summarize, even though changes in sectoral markups under variable markups are twice as large as the between-firm reallocation term for any firm-level shocks, variable markups do not necessarily magnify changes in sectoral markups relative to the model specification with constant markups, because incomplete pass-through mutes the extent of between-firm reallocation

3. Covariance Between Sectoral Prices and Sectoral Markups. Recall from previous results that in response to a positive shock to firm i in sector k , the sectoral price falls, whereas the sectoral markup can increase or decrease depending on the firm's initial markup. In finite samples, comovement can be positive or negative depending on which firms are shocked. We calculate the asymptotic covariance between sectoral price and markup changes, which shapes the covariance between sectoral output and markup that we examine below.

To build intuition, consider first the case of constant markups,

$$(23) \quad \mathbb{Cov} [\hat{\mu}_{kt}, \hat{P}_{kt}] = -\frac{1}{\varepsilon - 1} \sum_{i=1}^{N_k} s_{ki}^2 \left[1 - \frac{\mu_k}{\mu_{ki}} \right] \times \sigma_v^2.$$

Thus, sectoral markups and prices are negatively correlated as long as large firms in a sector charge higher markups. Intuitively, shocks to small firms induce a positive comovement, whereas shocks to large firms induce a negative comovement. Overall, comovement is negative because shocks to large firms induce larger changes in sectoral price than shocks to small firms.

With variable markups, using [equations \(18\) and \(21\)](#) we obtain

$$(24) \quad \begin{aligned} \mathbb{Cov} [\hat{\mu}_{kt}, \hat{P}_{kt}] &= -\left(\frac{2\mu_k}{\varepsilon - 1} \right) \left(\frac{1}{\sigma} - \frac{1}{\varepsilon} \right) \sum_{i'=1}^{N_k} s_{ki'}^2 \alpha_{ki'} \\ &\quad \times \sum_{i=1}^{N_k} \left[\frac{s_{ki}^2 \alpha_{ki}}{\sum_{i'=1}^{N_k} s_{ki'}^2 \alpha_{ki'}} - \frac{s_{ki} \alpha_{ki}}{\sum_{i'=1}^{N_k} s_{ki'} \alpha_{ki'}} \right] \\ &\quad \times \frac{s_{ki} \alpha_{ki}}{\sum_{i'=1}^{N_k} s_{ki'} \alpha_{ki'}} \times \sigma_v^2. \end{aligned}$$

When $\varepsilon > \sigma$, sectoral prices and markups comove negatively in long samples if and only if

$$(25) \quad \sum_{i=1}^{N_k} \left[\frac{s_{ki}^2 \alpha_{ki}}{\sum_{i'=1}^{N_k} s_{ki'}^2 \alpha_{ki'}} - \frac{s_{ki} \alpha_{ki}}{\sum_{i'=1}^{N_k} s_{ki'} \alpha_{ki'}} \right] \frac{s_{ki} \alpha_{ki}}{\sum_{i'=1}^{N_k} s_{ki'} \alpha_{ki'}} > 0.$$

If firms are ex ante homogeneous, [equation \(25\)](#) holds with equality and sectoral markups are constant over time. If firms are heterogeneous in the initial equilibrium, [inequality \(25\)](#) may or may not hold. The following proposition, proven in [Online Appendix A.3](#), states that if pass-through rates do not fall too strongly with market shares, [inequality \(25\)](#) holds, so sectoral prices and markups comove negatively.

PROPOSITION 2. Under Cournot competition, if firms are ex ante heterogeneous and $s_{ki}\alpha_{ki}$ is increasing in s_{ki} , the sectoral markup and price comove negatively, $\text{Cov} [\hat{\mu}_{kt}, \hat{P}_{kt}] < 0$.

In [Online Appendix A.2](#) we show that $s_{ki}\alpha_{ki}$ is increasing in s_{ki} provided that market shares are not too large. Intuitively, the condition that $s_{ki}\alpha_{ki}$ is increasing in s_{ki} implies, by [equation \(18\)](#), that sectoral prices are more responsive to large-firm shocks than to small-firm shocks (i.e., the lower pass-through rate by large firms does not fully offset their higher weight in the price index). The fact that sectoral markups increase in response to large-firm shocks and decrease in response to small-firm shocks implies a negative covariance between the sectoral price and markup, as in the case of constant markups.

4. Covariance Between Sectoral Output and Markups. Changes in sector k output in response to sector k shocks, derived in [Online Appendix A.4](#), are:

$$(26) \quad \begin{aligned} \hat{Y}_{kt} = & - \left[\sigma (1 - s_k) + \left(\frac{f+1}{f\eta+1} + \left(\frac{\sigma-1}{f\eta+1} \right) \left(1 - \frac{\mu}{\mu_k} \right) \right) s_k \right] \hat{P}_{kt} \\ & + \frac{s_k \mu}{\mu_k} \frac{\hat{\mu}_{kt}}{f\eta+1}. \end{aligned}$$

A sufficient condition for sectoral output and price to move in opposite directions is that sector k is small in the aggregate ($s_k \rightarrow 0$) or that disutility of labor is linear ($f \rightarrow \infty$). In this case, the previous results on the sectoral price apply immediately to sectoral

output (with the opposite sign).²¹ Specifically, in response to a positive shock to firm i in sector k , sectoral output increases, whereas the sectoral markup can increase or decrease depending on the firm's initial markup.

Taking into account a long sequence of firm shocks in sector k , the covariance between changes in sectoral output and sectoral markup is:

$$\begin{aligned} \text{Cov} [\hat{Y}_{kt}, \hat{\mu}_{kt}] = & - \left[\sigma (1 - s_k) + \frac{f + 1 + (\sigma - 1) \left(1 - \frac{\mu}{\mu_k}\right)}{f\eta + 1} s_k \right] \text{Cov} [\hat{P}_{kt}, \hat{\mu}_{kt}] \\ & + \frac{s_k \mu}{\mu_k} \frac{1}{f\eta + 1} \text{var} [\hat{\mu}_{kt}], \end{aligned}$$

where $\text{Cov} [\hat{P}_{kt}, \hat{\mu}_{kt}]$ is defined above. The following proposition provides sufficient conditions for procyclical sectoral markups with respect to sectoral output.

PROPOSITION 3. Under the conditions of [Proposition 2](#), sectoral markup and sectoral output comove positively, $\text{Cov} [\hat{Y}_{kt}, \hat{\mu}_{kt}] > 0$, if at least one of the following conditions holds: (i) $s_k \rightarrow 0$, (ii) $f \rightarrow \infty$, or (iii) $\sigma \rightarrow 1$. If (i)–(iii) are violated, then $\text{Cov} [\hat{Y}_{kt}, \hat{\mu}_{kt}] > 0$ as long as sectoral markup μ_k is not too low relative to the aggregate markup.

In the empirical analysis, we examine the cyclicity between sector output and firm-level markups. For the case of $f \rightarrow \infty$, we show that the covariance between changes in firm i markup and sector k output, derived in [Online Appendix A.4](#), is

$$\begin{aligned} \text{Cov} [\hat{Y}_{kt}, \hat{\mu}_{kit}] = & (\sigma (1 - s_k) + \eta^{-1} s_k) \frac{\alpha_{ki} \Gamma_{ki}}{(\epsilon - 1) \sum_{i'=1}^{N_k} s_{ki'} \alpha_{ki'}} \\ (27) \quad & \times \left[s_{ki} \alpha_{ki} - \frac{\sum_{i'=1}^{N_k} (s_{ki'} \alpha_{ki'})^2}{\sum_{i'=1}^{N_k} s_{ki'} \alpha_{ki'}} \right] \times \sigma_v^2. \end{aligned}$$

The following proposition states that firm-level markups are procyclical for large firms and countercyclical for small firms:

21. If f is finite and sector k is sufficiently large in the aggregate, it is possible that sectoral output and price both fall in response to positive sector k firm-level shocks if sectoral markup μ_k is very low relative to the aggregate markup and/or if sector k markup falls substantially when sectoral price falls.

PROPOSITION 4. If $s_{ki}\alpha_{ki}$ is increasing in s_{ki} and $f \rightarrow \infty$, firm-level markups and sectoral output comove positively, $\text{Cov}[\hat{Y}_{kt}, \hat{\mu}_{kit}] > 0$, if and only if $s_{ki} > \bar{s}_k^\mu$, and comove negatively if and only if $s_{ki} < \bar{s}_k^\mu$, where $\bar{s}_k^\mu$ is defined by the condition that the square bracket in [equation \(27\)](#) is equal to zero.

Intuitively, firm-level markups are positively correlated with sectoral output in response to own shocks and negatively correlated in response to competitors' shocks. Because large firms have a disproportionate effect on sectoral price and output (if $s_{ki}\alpha_{ki}$ is increasing in s_{ki}), firm-level markups are procyclical for large firms and countercyclical for small firms.²²

Before presenting the aggregate results, we briefly discuss the model's implications for changes in markups when some prices are nominally rigid.

5. *Discussion of Firm- and Sector-Level Markups with Rigid Prices.* Whereas we study markup fluctuations under flexible prices, markups can also fluctuate if costs change and prices are nominally rigid. Consider the specification under Bertrand competition and suppose that the price of firm i in sector k at time t is stuck at $\bar{P}_{kit}$ before the shocks hit.²³ For a sticky-price firm, the markup is $\mu_{kit} = \frac{Z_{kit}\bar{P}_{kit}}{W_t}$. For flexible-price firms (which do not anticipate that their price may be stuck in the future), markups are given by [equation \(5\)](#). Market shares for all firms are determined by the system of [equations \(4\)](#).

In response to productivity shocks to flexible-price firms, the sign of the change in sectoral markups depends on the relative markup level of the shocked firms, as in the baseline model. Consider now an increase in productivity of a rigid-price firm and suppose that the change in nominal wage is negligible. The markup of the shocked rigid-price firm rises mechanically, while markups of other firms remain unchanged (since prices and thus market shares do not change). Hence, the sectoral markup rises irrespective of whether the shocked firm is small or large. This force

22. The cutoff $\bar{s}_k^\mu$ differs from the cutoff defined in [Proposition 1](#) because the condition in [Proposition 1](#) is based on a shock to one firm only, whereas the asymptotic covariance in [Proposition 4](#) takes into account shocks to all firms in the sector.

23. Here for simplicity we take $\bar{P}_{kit}$ as given and do not study how firms choose their reset price. For a detailed analysis of sticky prices in a dynamic environment with oligopolistic competition, see [Mongey \(2021\)](#) and [Wang and Werning \(2022\)](#).

strengthens procyclical sectoral markups in comparison to the flexible-price model.

Now consider a uniform decline in marginal costs for all firms (productivity rises relative to the nominal wage). For firms with rigid prices, markups rise. For firms with flexible prices, markups also rise since these firms lower their price and increase market share relative to sticky-price firms. Hence, markups rise for all firms. There are additional compositional effects on the sectoral markup as market shares shift toward flexible-price firms. This composition effect increases the sectoral markup if flexible-price firms charge higher markups.²⁴ Whether the increase in markups is procyclical or countercyclical depends on the source of the movement in marginal cost. In response to an increase in productivity for all firms, markups and output rise. This force provides another reason for procyclical markups relative to the flexible-price baseline where, recall, sectoral shocks leave markups unchanged. In response to contractionary monetary policy that reduces marginal cost for all firms, markups rise but output falls, resulting in countercyclical markups. Our flexible-price baseline abstracts from this well-studied source of countercyclical markups.

III.C. Aggregate Outcomes

Here we characterize changes in the aggregate price (i.e., the inverse of the real wage, given that the wage is the numeraire), markup, productivity, and output. We provide expressions for the variance of aggregate output and for sectoral and aggregate markup cyclicalities with respect to aggregate output, which we consider in our empirical analysis.

Up to a first order, changes in the aggregate price are $\hat{P}_t = \sum_k s_k \hat{P}_{kt}$. Based on our foregoing results, any positive firm-level shock in sector k reduces the corresponding sectoral price and therefore reduces the aggregate price (or increases the real wage) proportionately to the share in expenditures of sector k . Whether the real wage increases more or less under variable markups relative to constant markups depends, as discussed already, on the shocked firm's relative size in its sector.

24. For evidence that prices are more flexible for large firms (which in our model charge higher markups), see [Goldberg and Hellerstein \(2009\)](#) and [D'Acunto et al. \(2018\)](#).

Changes in the aggregate markup can be decomposed into a within-sector markup term and a reallocation term, analogous to the decomposition of sectoral markups in [equation \(20\)](#):

$$(28) \quad \hat{\mu}_t = \sum_k s_k \frac{\mu}{\mu_k} \hat{\mu}_{kt} + (1 - \sigma) \sum_k s_k \left(1 - \frac{\mu}{\mu_k}\right) \hat{P}_{kt}.$$

In response to a positive shock to a firm in sector k , the aggregate markup can increase or decrease. The first (within) term in [equation \(28\)](#) is positive if the shocked firm is relatively large (and sets a higher markup) in sector k . The second (between) term in [equation \(28\)](#) is positive, when $\sigma > 1$, if sector k has a relatively high markup relative to the aggregate markup.

Changes in aggregate productivity, using $\hat{Z}_t = \hat{\mu}_t - \hat{P}_t$, can be expressed in terms of changes in sectoral markups and prices as

$$(29) \quad \hat{Z}_t = \sum_k s_k \frac{\mu}{\mu_k} \hat{\mu}_{kt} - \sum_k s_k \left[1 + (\sigma - 1) \left(1 - \frac{\mu}{\mu_k}\right)\right] \hat{P}_{kt}.$$

Finally, by [equation \(13\)](#), changes in aggregate output are

$$(30) \quad \hat{Y}_t = (f^{-1} + \eta)^{-1} \left[f^{-1} \hat{Z}_t - \hat{P}_t \right].$$

With linear disutility of labor ($f \rightarrow \infty$), the aggregate productivity term drops, so $\hat{Y}_t = -\eta^{-1} \sum_k s_k \hat{P}_{kt}$.

A positive firm-level shock in sector k reduces the sectoral price and increases aggregate output. Based on the discussion about the role of variable markups for the response of sectoral prices, the increase in aggregate output is smaller under variable markups compared with constant markups if and only if the shocked firm has a high market share.

1. *Variance of Aggregate Output.* The variance of aggregate output (when $f \rightarrow \infty$) is

$$(31) \quad \begin{aligned} \text{Var} \left[\hat{Y}_t \right] &= \eta^{-2} \sum_k s_k^2 \text{Var} \left[\hat{P}_{kt} \right] \\ &= \frac{\sigma_v^2}{\eta^2 (\varepsilon - 1)^2} \sum_k s_k^2 \sum_{i=1}^{N_k} \left(\frac{\alpha_{ki} s_{ki}}{\sum_{i'} \alpha_{ki'} s_{ki'}} \right)^2, \end{aligned}$$

where the second equality used [equation \(19\)](#). Based on the discussion after [equation \(19\)](#), aggregate output is less volatile under variable markups than under constant markups when pass-through rates are decreasing in size, effectively reducing the

weight of large firms in the price index (with similar effects on volatility as a reduction in market-share concentration).

In [Online Appendix A.6](#) we provide an expression for the variance of aggregate output without imposing $f \rightarrow \infty$, as well as for the variance of the aggregate markup, which we use in our quantitative analysis.

2. Covariance Between Aggregate Output and Markup. We first calculate the covariance between aggregate output and the sector k markup, which is one of the measures of cyclicalities in our empirical analysis. When calculating this covariance, we use the fact that sector k markups are affected only by shocks to sector k firms and not by shocks to firms in other sectors. We can thus express this covariance as

$$(32) \quad \text{Cov} [\hat{Y}_t, \hat{\mu}_{kt}] = \text{Cov} [\hat{Y}_{kt}, \hat{\mu}_{kt}] + \sigma (1 - s_k) \text{Cov} [\hat{P}_{kt}, \hat{\mu}_{kt}].$$

The following proposition, proven in [Online Appendix A.5](#), provides conditions under which the covariance between aggregate output and sector k markups is positive.²⁵

PROPOSITION 5. Under the conditions of [Proposition 3](#), $\text{Cov} [\hat{Y}_t, \hat{\mu}_{kt}] > 0$.

Finally, the covariance between aggregate output and the aggregate markup (when $f \rightarrow \infty$) is:

$$(33) \quad \begin{aligned} \text{Cov} [\hat{Y}_t, \hat{\mu}_t] &= -\frac{\mu}{\eta} \sum_k \frac{s_k^2}{\mu_k} \text{Cov} [\hat{P}_{kt}, \hat{\mu}_{kt}] \\ &+ \frac{\sigma - 1}{\eta} \sum_k s_k^2 \left(1 - \frac{\mu}{\mu_k} \right) \text{Var} [\hat{P}_{kt}]. \end{aligned}$$

The first term in [equation \(33\)](#) is positive if sectoral markups and sectoral prices comove negatively, which we discussed above. The second term in [equation \(33\)](#) is positive unless larger sectors have relatively lower markups.

25. Note also that by [equation \(32\)](#), $\text{Cov} [\hat{Y}_t, \hat{\mu}_{kt}] \leq \text{Cov} [\hat{Y}_{kt}, \hat{\mu}_{kt}]$, where the inequality holds strictly if the economy has more than one sector (i.e., $s_k < 1$). The fact that the covariance between sectoral markups and aggregate output is lower than that between sectoral markups and sectoral output does not immediately extend to correlations because for some sectors, the variance of aggregate output is smaller than the variance of sectoral output.

So far, we have calculated measures of markup cyclicalities considering only i.i.d firm-level shocks. In our quantitative analysis, we also allow for aggregate productivity shocks to firms in all sectors. In our model, in which firm-level markups are functions of market shares, markups do not respond to aggregate shocks. Therefore, incorporating aggregate shocks leaves the covariance of aggregate markups and output unchanged but decreases the correlation, because the volatility of aggregate output increases with these shocks.

From these theoretical results, we see that the sign of markup cyclicalities depends on the level of aggregation, market structure within and across all industries, and the set of shocked firms. Moreover, the sign and magnitude of covariances in finite samples may differ from those of the asymptotic covariances we derived.

In what follows we calibrate the model to match salient features of the French firm-level data. We use our calibrated model for two purposes. First, we evaluate quantitatively its implications for different measures of markup cyclicalities and compare these with their data counterparts. Second, we quantify aggregate fluctuations in output and markups in response to idiosyncratic firm-level shocks. Relative to the analytic results in this section, we relax some of the assumptions imposed in our propositions, solve the model nonlinearly, and calculate our moments in finite samples.

IV. DATA, ESTIMATION, AND CALIBRATION

For the remainder of this article, we use the model as a data-generating process from which we simulate firm-level outcomes, which are then aggregated into sector and aggregate time series. We then proceed to compare the resulting model-implied moments to their empirical counterparts. This section describes how we use French administrative firm-level data to obtain empirical moments of interest and parameterize our model. We describe the data, how we estimate markups, and how we calibrate the model. [Online Appendix B](#) provides additional information on the data and the procedures to estimate production functions and markups.

IV.A. Data

Our empirical analysis deploys French firm-level data between 1994 and 2019. We use administrative sources for income statements and balance sheets, complemented by a firm survey with information on quantities.

Firm-level income statements and balance sheet data are obtained from two administrative data sets: the FICUS data covering 1994–2007 and the FARE data set covering 2008–2019. These data sets cover the universe of French firms and originate from the French tax administration, which collects yearly tax statements for each firm, including income statements, balance sheet, and demographic information. The Institut National de la Statistique et des Etudes Economiques (INSEE) uses these statements to construct the FICUS-FARE data sets. We assign firms to sectors according to the Nomenclature d'Activités Française (NAF2008) five-digit classification, a French industry classification similar to the four-digit NACE Rev 2 classification. We keep firms that were government-owned earlier in our sample since during the period we consider most of them switched to private ownership.²⁶

We use a subset of the variables available in the FICUS-FARE data set: total firm revenues, wage bill (the sum of wages and social security payments), capital (measured by fixed assets), and expenditures on both material and service inputs. Our baseline measure of materials (which is our choice of variable input in the estimation of markups) is the sum of expenditures on materials and merchandises (variables *ACHAMPR* and *ACHAMAR*, respectively) net of changes in stocks (*VARSTMP*

26. In 2008, the NACE and NAF industry classification changed. To construct a panel of firms between 1994 and 2019 with a consistent industry classification over time, we proceed as follows. For firms for which the old and new industry codes are observed, we apply the new code to all years. For firms for which we only observe one industry code on either side of 2008, we assign the code that is most frequently associated with the observed industry code (using the sample of firms where we do observe the two sectoral codes). Finally, information about government-owned firms can be found in the variable *APPGR* of FICUS-FARE, which is available only before 2009. Government-owned firms represented 0.12% of the total number of firms in 1994 and 0.05% in 2008. Over the same period, their share of revenue fell from 7.2% to 4.2%. We thank Isabelle Méjean for sharing the computer code to merge the FICUS and FARE data sets.

for materials and *VARSTMA* for merchandise).²⁷ We consider as a separate input expenditures on service inputs (*AUTACH*), including research expenditures, outsourcing costs, and external personnel cost (including temporary workers). We use GDP deflators and two-digit sector-price indices provided by EU-KLEMS.

We construct a measure of firm-level quantity using the survey *Enquête Annuelle de Production* (EAP) conducted by INSEE. Specifically, this survey covers the universe of large firms (with at least 20 employees or €5 million in annual revenues) and a representative sample of small firms for a subset of two-digit sectors, mainly in manufacturing, during 2009–2019.²⁸ For each firm, this data set provides information on revenues and quantities by product, where a product is a combination of an eight-digit code and a unit of account.²⁹ We drop around one-third of firm-products without quantity data. We calculate price by product for each firm as the ratio of revenues to quantity sold. We follow [De Ridder, Grassi, and Morzenti \(2024\)](#) and [Aghion et al. \(2023\)](#) in standardizing prices by dividing them by the quantity-weighted average price of the same product across firms in the same year. We do this because firms produce goods in different units (e.g., kilograms and liters), and aggregation requires homogeneous units. Our measure of firm-level price in a given year is the revenue-weighted average of standardized prices across the products the firm sells. Finally, firm-level quantity is defined as the ratio of firm-level revenues to firm-level price.

27. The variable *ACHAMPR* is defined as “everything that the firm purchases in order to be transformed,” and *ACHAMAR* is defined as “everything that the firm purchases to be sold as is.” *VARSTMP* and *VARSTMA* are defined analogously for changes in stocks.

28. The EAP survey is used by EUROSTAT to produce statistics such as Structural Business Statistics and Production Statistics. According to INSEE, roughly 35,000 unique firm identifiers are included in this survey, covering 90% of French industrial production. The two-digit NACE rev 2 sectors covered by our EAP sample are 08, 13, 14, 15, 16, 17, 18, 20, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 43, and 46, where the last two are nonmanufacturing sectors (“specialized construction activities” and “wholesale trade, except of motor vehicles and motorcycles,” respectively).

29. Examples of units of accounts are kilograms, tonnes, or pieces. We define a product as a combination of a unit of account and product code because firms that use different units of accounts for the same product code might produce relatively heterogeneous goods.

For the rest of the article, it will be useful to distinguish two samples: (i) the sample of firms with quantity information in the EAP data set, which we use to estimate two-digit sector-level production functions; this will form the basis of our estimation sample; and (ii) the sample of all firms in FICUS-FARE that belong to sectors covered by the EAP data set—including those with revenues but no quantity data—used to calculate our measures of markup cyclicalities, which we treat henceforth as our baseline sample.

For the first sample, which covers 2009–2019, we keep firms with more than two employees and with positive value added, revenue, materials, services expenditure, wage bill, capital, and price. We winsorize these variables by sector at the 1% level. We end up with 220,733 firm-year observations across 11 years and 22 sectors at the two-digit level. Despite the smaller number of observations and shorter time span, the estimation sample represents about 38% of value-added in the baseline sample. For the second sample, which covers 1994–2019, we keep firms with positive value added, revenue, materials, services expenditure, wage bill, and capital. We further restrict the sample to firms with positive estimated gross markups (estimated as described below).³⁰ This yields a firm-level panel with 9,383,228 observations, covering 26 years, 22 sectors at the two-digit level, and 275 sectors at the five-digit level. [Online Appendix Table A1](#) displays further summary statistics for the estimation sample (Panel A) and the baseline sample used to measure markup cyclicalities (Panel B). Firms in the estimation sample are larger than firms in the baseline sample because the EAP survey focuses on large firms. The average market share across all firms and years is low, at about 0.07%. However, the distribution of market shares is highly skewed, with the top 0.01% attaining a market share above 38%.

Although this data set is very rich, it misses some important information that limits the extent of our analysis. First, we do not use information on imports and exports in the corresponding sector. Specifically, when we compute market share as the ratio of a firm's revenue relative to the sum of all French firms' revenue in this sector, we do not take into account the sales of for-

30. Market shares (defined as the share of firm-level revenues in the corresponding five-digit sector), sectoral aggregates, and HHIs are calculated before restricting the sample.

eign firms in this market. Moreover, when we estimate markups, we do not exclude sales to foreign countries because we do not know the share of expenditures on inputs that is accounted for by exports.

Second, because firm-level revenues in our data set are reported at the national level, we do not have information on revenues at the local level. This limitation is important for non-tradable goods, whose markets are most likely local.³¹ Because our definition of a market is at the national level, for non-tradable goods we likely underestimate the concentration in the local market relevant for the firm.

IV.B. Markup Estimation

We estimate markups for two purposes. First, we calculate measures of markup cyclicalities in the data, which we compare with markup dynamics implied by our model. Second, when we calibrate the model, we target the relationship between sectoral markups and HHI.

Our empirical framework to estimate markups in the data is more general than our theoretical framework described above, where labor was the only factor of production. Specifically, we include materials, capital, and services as inputs to production.³² We assume that materials, M , are chosen statically (i.e., they are not subject to adjustment costs). Following Hall (1988) and De Loecker and Warzynski (2012), the first-order condition for M in the cost-minimization problem by firm i in sector k implies

$$(34) \quad \mu_{kit} = \theta_{kit}^M \frac{P_{kit} Y_{kit}}{P_{kit}^M M_{kit}},$$

where $P_{kit}^M M_{kit}$ denotes expenditure on materials by firm i in sector k , $P_{kit} Y_{kit}$ is revenues, and θ_{kit}^M is the output elasticity with respect to materials. To measure markups at the firm level, we require the ratio of material expenditures to revenues—which is available for all firms in our baseline sample—and the output elasticity with respect to materials.

31. See Rossi-Hansberg, Sarte, and Trachter (2020) for a study of diverging local and national market concentration trends or Smith and Ocampo (2025) for the evolution and consequences of market concentration trends in the U.S. retail sector.

32. We maintain the assumption that firms are price takers in input markets. Morlacco (2019) relaxes this assumption to estimate markdowns on inputs.

To estimate output elasticities, we assume a flexible translog production function with the four inputs already described. All firms in the same two-digit sector share the same production-function parameters and—constrained by the availability of two-digit-level price indices for intermediate inputs—inputs are homogeneous across firms in a sector. The output elasticity with respect to materials of firm i in market k at time t is equal to $\theta_{kit}^M = \beta_m + 2\beta_{mm}m_{kit} + \beta_{ml}l_{kit} + \beta_{mo}o_{kit} + \beta_{mk}k_{kit}$, where the β_{xy} are the parameters of the production functions and m_{kit} , l_{kit} , o_{kit} , and k_{kit} are, respectively, the firm-level log materials, labor, service, and capital usage. Note that output elasticities differ across firms in two-digit sectors even if these firms have the same production function parameters β .

We estimate the parameters in the production function implementing a two-stage iterative generalized method of moments (GMM) following [De Ridder, Grassi, and Morzenti \(2024\)](#), which builds on [Olley and Pakes \(1996\)](#), [Levinsohn and Petrin \(2003\)](#), [Akerberg et al. \(2007\)](#), and [Akerberg, Caves, and Frazer \(2015\)](#). Here we provide an overview of our approach, and [Online Appendix B.2](#) provides additional details. The first stage of this method controls for unobserved productivity by using conditional demand of material input. As discussed in [Doraszelski and Jaumandreu \(2019\)](#) and [De Ridder, Grassi, and Morzenti \(2024\)](#), under imperfect competition of the form considered here, this first-stage requires additional controls, namely, market share and firm-level price. In the second stage, we implement a dynamic panel estimator using GMM. Importantly, in both stages we use quantity data as our output measure, thus we can only implement this approach in our estimation sample of firms.

Finally, assuming (i) that all firms in the same two-digit sector (including those with and without quantity information) share the same production function parameters and (ii) that these parameters are stable over time allows us to apply the parameters obtained in the estimation sample to all FICUS-FARE firm-year observations in the corresponding sectors and compute output elasticities in the longer and larger baseline sample.

Equipped with output elasticities and material-to-revenue ratios, we calculate markups in the baseline sample using expression (34). [Online Appendix Table A1](#) provides descriptive statistics of our firm-level markup estimates. The distribution of markups is quite skewed, with a median of 1.21, a mean of 1.39, and a top quartile of 1.77.

Given our use of quantity as a measure of output, our estimates are not subject to biases that may emerge when revenues are used, as discussed in [Bond et al. \(2021\)](#), [Anderson, Rebelo, and Wong \(2023\)](#), and [De Ridder, Grassi, and Morzenti \(2024\)](#). Nevertheless, in [Section VI.D](#) we provide sensitivity analysis on the use of quantity, revenue, or accounting data to compute markups and measure markup cyclicity.

IV.C. Calibration

Here we describe how we parameterize the model to match salient features of the French data. We introduce the firm-level productivity stochastic process. We describe our calibration strategy, which targets the size and concentration of each of the 275 sectors at the five-digit level together with other moments from our data and the literature.

1. *Firm-Level Productivity Process.* We assume that firm-level quality shifters, A_{kit} , are fixed over time so that the firm-shifter V_{kit} is driven only by productivity shocks.³³ Following [Carvalho and Grassi \(2019\)](#), we assume that firm-level productivity, Z_{ikt} , follows the discretized random growth process introduced by [Córdoba \(2008\)](#). Specifically, firm productivity in sector k evolves on an evenly spaced log grid, $\Phi_k = \{1, \varphi_k, (\varphi_k)^2, \dots, (\varphi_k)^S\}$, where $\varphi_k > 1$ and S is an integer. A firm's productivity follows a Markov chain on this grid with associated transition matrix $\{P_{n,m}^{(k)}\}_{n,m \in [1,S]}$ such that $P_{n,n}^{(k)} = 1 - a_k - c_k$, $P_{n,n-1}^{(k)} = a_k$, $P_{n+1,n}^{(k)} = c_k$, $P_{1,1}^{(k)} = a_k + b_k$, and $P_{S,S}^{(k)} = b_k + c_k$ with $1 > a_k, b_k, c_k > 0$ and $a_k + b_k + c_k = 1$. The three parameters φ_k , δ_k , and c_k characterize this productivity process in sector k .

As shown in [Córdoba \(2008\)](#) and [Carvalho and Grassi \(2019\)](#), this process implies Gibrat's law for productivity. That is, away from the boundaries, productivity growth is independent of its current level. In addition, this process generates a stationary Pareto distribution of productivity ([Gabaix 1999](#)) with a tail index equal to $\delta_k = \frac{\log(\frac{a_k}{c_k})}{\log(\varphi_k)}$. Note, however, that in our environment this

33. Although our analytic results do not take a stand on the importance of productivity versus quality-shifter firm-level shocks, in the data we construct sectoral output deflating nominal value-added by industry price indices. The latter typically do not take into account high-frequency changes in quality shifters. Therefore, for consistency, in the data we abstract from shocks to quality shifters.

TABLE I
CALIBRATION TARGETS

Moment	Source	Data	Model
Panel A: Economy-wide targets			
Slope of $\Delta\mu_{t,k}^{-1}$ on $\Delta HHI_{t,k}$	Table V	-0.37	-0.36
Constant of volatility on market share	Table A5	0.27	0.27
Panel B: Sectoral targets			
Number of firms $N_k^{(*)}$	Baseline sample	1,453	1,453
Revenue share $^{(*)}$	Baseline sample	0.16%	0.16%
HHI (See Figure I) $^{(*)}$	Baseline sample	0.115	0.115

Notes. Rows with $^{(*)}$ refer to 275 moments (one per five-digit sector). We report averages across the 275 sectors.

does not immediately imply that firm size satisfies these properties due to the finite number of firms within sectors and variable markups.

In Section VII, we consider an exercise where we add aggregate TFP shocks to target the volatility of annual changes in aggregate output.

2. *Calibration Strategy.* We describe how we assign values to the model’s parameters: the two macro parameters η and f , the two demand elasticities ε and σ , the number of firms N_k , the demand shifter A_k , and the productivity parameters φ_k , δ_k , and c_k for our 275 sectors. Table I and Figure I summarize data targets and model fit, while Table II displays parameter values.

We set the relative risk aversion to one (log utility) and the Frisch labor-supply elasticity to one, both of which are standard values in the business cycle literature. We assume that in all sectors, firms compete à la Cournot. We set the within-sector elasticity to $\varepsilon = 5$.³⁴ We calibrate the between-sector elasticity σ to target the slope of the regression in first differences (over time) of the inverse sectoral markup on the HHI (constructed as described in Section V). In the data, the coefficient of this regression is -0.37 , as reported in Table V, column (2). In the model, taking first differences of equation (8) implies $\Delta\mu_{tk}^{-1} = -\frac{(\frac{\varepsilon}{\sigma}-1)}{\varepsilon}\Delta HHI_{tk}$.

34. In Online Appendix F we provide sensitivity analysis for alternative values of ε ranging between four and seven while recalibrating the remaining model parameters. Our quantitative results on markup cyclicity are fairly stable, while aggregate output volatility is increasing in ε .

TABLE II
BASELINE CALIBRATION

Parameters	Value	Description
Panel A: Economy-wide parameters		
η	1	Relative risk aversion
f	1	Frisch elasticity of labor supply
f_0	1	Labor disutility parameter
ε	5	Substitution across firms
σ	1.8	Substitution across sectors
Panel B: Sectoral parameters		
S	70	Number of productivity bins per sector
φ_k	1.091	Median firm-level productivity process
a_k, c_k	0.348, 0.250	Median firm-level productivity process
A_k	0.0015	Median sectoral preference shifter

Given our choice of ε , we set $\sigma = 1.8$, which implies a slope of -0.36 . The two demand elasticities σ and ε shape own-cost pass-through rates $\tilde{\alpha}_{ki}$, defined in footnote 18. Our baseline choices imply an own-cost pass-through rate of 0.63 for large firms (those with a market share of 57% or higher), which lies within confidence intervals in [Amiti, Itskhoki, and Konings \(2019\)](#) for large Belgian firms.³⁵

Now we discuss how we assign parameter values that vary across the 275 sectors to match salient features of our data in 1994–2019. We set the number of firms per sector, N_k , to the average number of firms in sector k observed in our data. We calibrate the constant sector-level demand shifter, A_k , to target the average revenue share of the 275 sectors in the data. For each sector k , we choose the tail parameter of the stationary distribution, δ_k , to match the average HHI in the data. [Figure I](#) reports HHI in the data against the model counterpart. The fit is good, as

35. About 360 firm-year observations have a market share above 57%, representing approximatively the top 0.004% of the market share distribution. Our model implies pass-through rates that are on the high end of estimates in [Amiti, Itskhoki, and Konings \(2019\)](#) for Belgian firms and on the low end of estimates in [Berman, Martin, and Mayer \(2012\)](#) for French exporters and is consistent with findings in both papers that pass-through rates are decreasing in firm size. For alternative values of ε reported in [Online Appendix F](#), pass-through rates are lower (e.g., 0.55 for large firms when $\varepsilon = 7$) and thus closer to the point estimates in [Amiti, Itskhoki, and Konings \(2019\)](#).

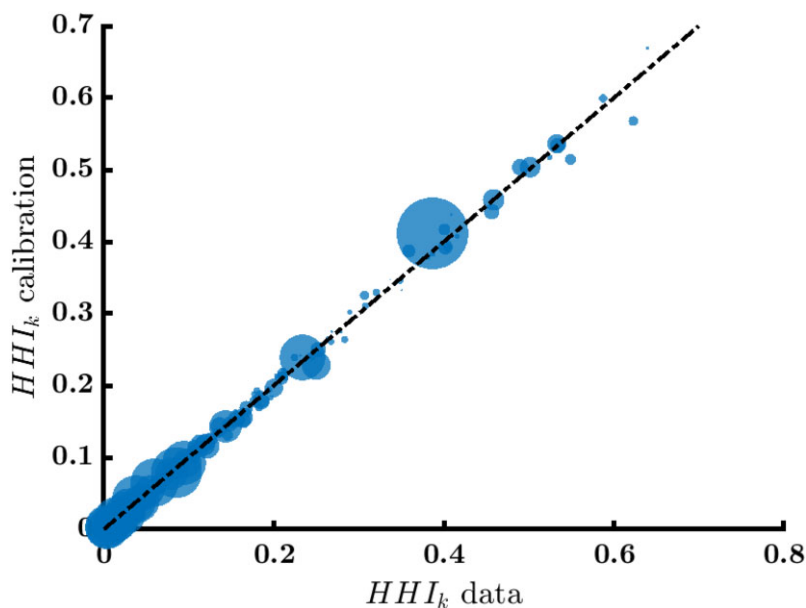


FIGURE I
Model Fit

For each sector, this figure shows the HHI in the data (x-axis) against the median HHI computed over 1,000 samples drawn from the baseline calibration (y-axis). The size of each dot is proportional to the sector's average revenue share between 1994 and 2019.

revealed by the fact that all dots lie close to the 45-degree line.³⁶ The grid parameter φ_k determines the range of values that the HHI can take as we vary δ_k . We choose the lowest φ_k such that this range of values contains the value of the HHI in the data for this sector.³⁷ Finally, we set the remaining parameter of the productivity process, c_k , such that in each sector the conditional volatility of market share for a hypothetical infinitesimal firm is equal to the constant in the regression of market-share volatil-

36. Given a guess of δ_k , we draw 1,000 samples of N_k firm-level productivities from the Pareto distribution characterized by δ_k . For each sample, we solve for firm-level market shares and compute the implied HHI. We calculate the median HHI across the 1,000 samples and iterate over δ_k until we match the HHI for a given sector in the data. We repeat this procedure for the 275 sectors.

37. We choose the number of productivity bins $S = 70$. Higher values of S have a minor effect on our results.

ity on market share estimated across all sectors in the data and reported in [Online Appendix Table A5](#).³⁸

In what follows we use the calibrated model as a data-generating process to simulate firm-level, sector-level, and aggregate-level time series. We use the simulated panels to run the corresponding regressions that we run on actual data. We also compute aggregate business cycle statistics using the simulated aggregate time series, which we compare with counterparts in the data.

V. INSPECTING THE MECHANISM

Here we examine in the data some basic implications of our model. We analyze the relation between firm-level markups, marginal costs, and market shares within sectors, as well as that between sectoral markups and measures of concentration across sectors. We also quantify the contribution of changes in firm-level markups for sector-level markup changes.

V.A. Firm-Level Evidence

Hardwired into our model is a key micro-level relationship between markups and concentration. At the firm level, following the discussion in [Section II.B](#), markups increase with a firm's market share. In turn, this immediately gives rise to a notion of markup procyclicality at the micro level: a firm's markup increases whenever its market share increases.

Taking the inverse of [equation \(5\)](#) and applying first differences yields a simple linear relation between the firm's market share and its inverse markup,

$$(35) \quad \Delta\mu_{kit}^{-1} = -\frac{\frac{\varepsilon}{\sigma} - 1}{\varepsilon} \Delta s_{kit},$$

where $\Delta\mu_{kit}^{-1}$ is the first difference of the inverse (gross) markup of firm i in sector k at time t and Δs_{kit} is the first difference of its market share. This motivates the following simple empirical

38. For each firm in our baseline sample, we calculate the time-series standard deviation of the firm's market share growth rate. [Online Appendix Table A5](#), column (1) reports a regression of this volatility measure on average market share and a constant term. In column (2) we report an alternative specification using the standard deviation of the growth rate of market share in the cross section, as explained in the notes to [Online Appendix Table A5](#). Both specifications yield a precisely estimated constant of approximately 0.27.

specification,

$$(36) \quad \Delta\mu_{kit}^{-1} = \alpha_t + \beta\Delta s_{kit} + \epsilon_{kit},$$

where β is the coefficient of interest, which the model predicts to be negative. We allow for year fixed effects α_t to control for unobserved markup shifters that are common across all firms. In alternative specifications we further allow for sector-year fixed effects, α_{kt} , thus absorbing markup variation that is common across all firms in a sector, in a given year. While these fixed effects are not present in our theoretical model, they nevertheless allow us to empirically control for flexible aggregate and sector-specific markup trends in the data and serve as a robustness check.

We start by inspecting these firm-level relations in the French data. We have estimates of firm-level markups over the period 1994–2019, as described in the previous section. We calculate firm-level market shares as the ratio of firm-level revenues to total revenues in the corresponding five-digit sector. Taking first differences yields time series for $\Delta\mu_{kit}$ and Δs_{kit} for 955,657 unique firms over the period 1995–2019.

Table III displays our estimates and the associated two-way (at firm and year level) cluster-robust standard errors. Column (1) displays the firm-level relation in first differences, obtained by pooling all firm-level data (across sectors and years) for a total of over 8 million observations. This yields a negative and statistically significant coefficient, as theory predicts. Further, the empirical estimates remain stable and significant when additionally controlling for year (column (2)) and sector-year (column (3)) fixed effects. Finally, as a further robustness check, in Online Appendix Table A6 we report estimates for an alternative specification that regresses firm markups on firm market shares in levels, allowing for firm fixed effects. The estimates are again similar to those in first differences in Table III, columns (1) and (2).

The data are therefore consistent with changes in a firm's market share acting as a proximate driver of its markup dynamics, as predicted by theory. Notice that ultimately, in the model a firm's market share and markup are jointly determined in equilibrium by exogenous firm-level technology (and/or quality) shifters. All else constant, a decrease in firm's marginal cost relative to that of its competitors will increase its competitiveness in the product market and, hence, its market share (and therefore

TABLE III
INVERSE MARKUP AND MARKET SHARE

Dependent variable	$\Delta\mu_{kit}^{-1}$		
	(1)	(2)	(3)
Δs_{kit}	−0.268 (0.092)	−0.268 (0.093)	−0.293 (0.099)
Year FE	N	Y	N
Sector × year FE	N	N	Y
Observations	8,051,767	8,051,767	8,051,767

Notes. $\Delta\mu_{kit}^{-1}$ is the first difference of the inverse of firm i sector k gross markup between t and $t - 1$, and Δs_{kit} gives the first difference of market share of firm i in sector k . Columns (1)–(3) report baseline empirical estimates for the FICUS-FARE (1995–2019) data. Column (1) reports pooled estimates, while columns (2) and (3) report estimates that further control for year or sector × year fixed effects, respectively. Sector-year fixed effects are defined at the five-digit NAF sector classification. Standard errors (in parentheses) are two-way clustered at the firm and year level. $\Delta\mu_{kit}^{-1}$ is winsorized at the 3% level.

TABLE IV
MARKUPS, MARKET SHARES, AND MARGINAL COSTS

Dependent variable	$\Delta \log s_{kit}$			$\Delta \log \mu_{kit}$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \log mc_{it}$	−0.022 (0.003)	−0.022 (0.003)	−0.023 (0.003)	−0.091 (0.008)	−0.091 (0.009)	−0.096 (0.009)
Year FE	N	Y	N	N	Y	N
Sector × year FE	N	N	Y	N	N	Y
Observations	178,368	178,368	178,368	178,368	178,368	178,368

Notes. $\Delta \log \mu_{kit}$ is the first difference of (log) gross markup of firm i sector k at time t , $\Delta \log s_{kit}$ is the first difference of (log) market share, and $\Delta \log mc_{it}$ is the first difference of (log) marginal cost when the latter is defined as the difference between (log) price and (log) markup of firm i in sector k at time t . All columns report empirical estimates for the estimation sample FARE (2009–2019) data. Columns (1) and (4) report pooled estimates, while columns (2), (3), (5), and (6) report estimates that further control for year or sector × year fixed effects. Sector-year fixed effects are defined at the five-digit NAF sector classification level. Standard errors (in parentheses) are two-way clustered at the firm and year level. $\Delta \log \mu_{kit}$ and $\Delta \log mc_{it}$ are winsorized at the 3% level.

its markup, as above). We now turn to assessing this relation in the data.

Recall from [Section IV.B](#) that for the estimation sample, we can obtain both firm-level price data, P_{kit} , and markup estimates, μ_{kit} . Given this, for firms in this smaller estimation sample we can exploit the relation $\frac{P_{kit}}{\mu_{kit}} = mc_{kit}$ to back out an empirical proxy of firm-level marginal costs. We can thus inspect the model-implied predictions regarding marginal costs, market shares, and markups, albeit in a significantly smaller sample. [Table IV](#) reports empirical estimates of simple OLS regressions of firm-level

market share and markup growth rates on the growth rates of our firm-level marginal cost proxy.

Starting with the simple bivariate relation between marginal cost growth and market share growth, our estimates in column (1)—where we pool data across all sectors and years—imply that a 1% year-on-year increase in firm-level marginal costs is associated with a small but significant 0.02% decrease of a firm's market share growth. This estimate is robust to additionally controlling for average economy-wide marginal cost dynamics (i.e., the year fixed effects specification in column (2)) or the average marginal cost growth across competitors in a given firm's sector (i.e., the sector-year fixed effects specification in column (3)). The last three columns of [Table IV](#) complete the argument by inspecting the relation between firm-level marginal cost growth and firm-level markups. Again, we observe that year-on-year increases in marginal costs result, as our model with incomplete pass-through predicts, in lower markups both unconditionally (in column (4)) and when conditioning on year or sector-year fixed effects in columns (5) and (6), respectively. Finally, in [Online Appendix Tables A7 and A8](#) we verify that these empirical estimates are robust to considering an alternative specification in levels (rather than growth rates) with firm fixed effects.

The negative correlation between markups and marginal cost reported in [Table IV](#) may be spurious if markups are subject to measurement error, since marginal costs are measured as the ratio of prices to markups.³⁹ To address this concern, in [Online Appendix E.3](#) we construct a proxy for marginal cost based on energy prices and a firm's reliance on energy as an intermediate input. Following [Ganapati, Shapiro, and Walker \(2020\)](#), the rationale for this proxy is that energy price changes are exogenous to the firm but are nevertheless relevant for the evolution of a firm's marginal cost, depending on a firm's energy intensity. Using this proxy as an instrument for marginal cost, [Online Appendix Table A10](#) confirms that higher marginal cost is associated with lower markup and lower market share, with larger point estimates than in our OLS specification.

Taken together, we conclude that our data is consistent with the basic qualitative firm-level predictions of our model.

39. Unlike this specification, other regressions in the article include markups in the left side—rather than as an independent variable—so measurement error bias is less of a concern.

V.B. Sector-Level Evidence

As discussed in [Section II.C](#), equilibrium aggregation of firm-level outcomes yields additional predictions at the sector level. First, note that by the same logic as before, taking the inverse of [equation \(8\)](#) and then first differences yields the following relation between inverse sectoral markup and a sector's HHI:

$$(37) \quad \Delta\mu_{kt}^{-1} = -\frac{\frac{\varepsilon}{\sigma} - 1}{\varepsilon} \Delta HHI_{kt},$$

where $\Delta\mu_{kt}^{-1}$ is the first difference of the inverse (gross) markup of sector k at time t and ΔHHI_{kt} is the first difference of its HHI. This yields a sector-level counterpart to [equation \(35\)](#) where inverse sectoral markups now comove linearly with sectoral concentration.

To assess this relationship in the data, we consider the following empirical specification:

$$(38) \quad \Delta\mu_{kt}^{-1} = \alpha_t + \beta \Delta HHI_{kt} + \epsilon_{kt},$$

where β is the coefficient of interest. We allow for year fixed effects α_t and also consider robustness to the inclusion of broad two-digit sector-year fixed effects. Finally, in [Online Appendix E.2](#), we report estimates based on a levels specification and sector-level fixed effects.

To construct sectoral markups in the data for our 275 narrowly defined five-digit sectors, we aggregate firm-level markups to their sector-level counterparts by taking a harmonic market-share weighted average of firm-level markups—as indicated by the model [equation \(7\)](#). For each five-digit sector, we construct the HHI by summing up the square of firm-level market shares. We take first differences across time periods of both the sector-level markup and the HHI series. This results in a balanced panel of 275 sectors at the five-digit level across 25 years for a total of 6,875 observations.

[Table V](#), column (1) displays estimates of a pooled regression across all sectors and years. Our estimates indicate a negative and significant relation between the change in concentration and the change in the inverse of sector markups. The estimates remain stable when additionally considering year or broader two-digit sector-year fixed effects in columns (2) and (3). The point estimate is about -0.37 which, recall, is the target in our calibration. [Online Appendix Table A9](#) reports alternative specifications in levels rather than growth rates.

TABLE V
SECTOR INVERSE MARKUP AND SECTOR HHI

Dependent variable	$\Delta\mu_{kt}^{-1}$		
	(1)	(2)	(3)
ΔHHI_{kt}	−0.374 (0.177)	−0.370 (0.178)	−0.378 (0.180)
Year FE	N	Y	N
Sector (2D) × year FE	N	N	Y
Number of sectors	275	275	275
Observations	6,875	6,875	6,875

Notes. $\Delta\mu_{kt}^{-1}$ is the first difference of sector k (inverse) markup in year t , ΔHHI_{kt} is the first difference of HHI in sector k . Columns (1)–(3) report empirical estimates for the FICUS-FARE (1995–2019) data, aggregated to the five-digit NAF sector level. Column (1) reports pooled estimates, while columns (2) and (3) report estimates that further control for year or broad two-digit-sector × year fixed effects, respectively. Standard errors (in parentheses) are two-way clustered at the sector and year level. Underlying firm-level inverse markups are winsorized at 3%.

Note that our model also imposes cross-equation restrictions. Compare [equations \(35\) and \(37\)](#): the slope coefficients of these two relations—that is, the slope of the inverse of firm markup on market share and the slope of the inverse sector markup on sector HHI—should coincide. Comparing point estimates across [Tables III and V](#) suggests that the implied slopes are indeed similar: focusing on the more demanding sector-year fixed effects specifications, we obtain slopes of -0.293 and -0.378 , respectively, with both estimates falling within (less than) one standard error of each other.

Finally, recall that in our model, changes in sectoral markups reflect two forces. First, for given firm market shares, the evolution of endogenous firm-level markups may lead to changes in aggregated, sector-level markups. Second, for given heterogeneous firm-level markups, equilibrium reallocation of market shares also affects sector markup dynamics. Specifically, note that following [equation \(7\)](#), the change in sectoral markups between two time periods can be written as

$$\Delta\mu_{kt}^{-1} = \sum_{i=1}^{N_k} \Delta\mu_{kit}^{-1} \bar{s}_{kit} + \sum_{i=1}^{N_k} \Delta s_{kit} \bar{\mu}_{kit}^{-1},$$

where Δ denotes the year-on-year difference and bars denote averages over two consecutive years. This yields a standard within-between decomposition of sectoral markup changes. The first term on the right side gives the within term, measuring the

change in (inverse) sectoral markup due to changes in firm-level markups, evaluated at the average market share of each firm. The second term on the right side is the between or reallocation term: it measures the change in the (inverse) sectoral markup due to the changes in firm market share, evaluated at a firm's average (inverse) markup. As discussed in [Section III.B](#) and shown in [Online Appendix A.1](#), in the model under Cournot competition the within and between terms are equal to each other in every sector. From this result, it follows that under Cournot, the contribution of the within and between/reallocation terms are each predicted to be equal to 50%.

Given time series of firm-level markups and market shares in the data, the within-between decomposition can be readily computed. To do this, for each sector we regress the within term over time on changes in the sector-level markup. The coefficient of this regression is the contribution of the within term to the evolution of sector-level markups.⁴⁰ We find that for the median sector in the French data the within term accounts for 59% of the changes in sector markups, close to the model prediction of 50%. Although there is heterogeneity in the data, for half of the sectors in France the contribution of the within term lies between 34% and 81%. Overall, taking firm and sector evidence together, the data is consistent with key predictions of the model.

VI. MODEL MEETS DATA: REDUCED-FORM VARIETIES OF MARKUP CYCLICALITY

Our theoretical framework yields a simple relation between markups and size: the level of a firm's markup is determined by its market share in a sector. In turn, both markups and market shares are driven by firm-level marginal cost shifters. The aggregation of within-firm endogenous markup changes and reallocation of market shares across firms determines sectoral markups and sectoral concentration, yielding a linear relation between a sector's (inverse) markup and its concentration. As we have seen, the data broadly support these model-implied relations.

40. In the data, the reallocation term (defined as the difference between the change in (inverse) sectoral markup and the within term) captures not only changes in market share across continuing firms but also churn as some firms enter and exit the market each year.

By contrast, a large applied literature investigates different definitions of markup cyclical. The evidence is mixed on whether markups are procyclical or countercyclical. In this section, we argue that these conflicting empirical results can be at least partly ascribed to the alternative reduced-form exercises and definitions of markup cyclical. We show that our model with firm-level shocks only can go a long way in accounting for these seemingly conflicting reduced-form relations in the data.

VI.A. Firm-Level Markup Cyclical with Sector Output

We start by analyzing a firm-level notion of reduced-form markup cyclical and ask how firm markups covary with the respective sector-level output.

Before going to the data, recall that our setting is a granular one in which extensive within-sector heterogeneity in the firm-size distribution enables large firm dynamics to lead the sectoral business cycle. In particular, in our setting with idiosyncratic firm-level shocks—and if pass-through rates do not fall too strongly with market shares—sector-output fluctuations are necessarily led by shocks to very large firms. To make matters concrete, consider a reduction in marginal cost for a large market share firm. Given the granular nature of the economy, the corresponding sector output will typically increase (see [equation \(26\)](#)). In addition, the large shocked firm will increase its market share and markup. This implies, as indicated in [Proposition 4](#), that markups of large firms should comove positively with sector output.

By the same token, the average (small) firm in a given sector loses market share to the very largest firms: if sector-level output expansions are led by large firms, the latter will increase their market share whereas the average firm loses competitiveness—as evaluated by its market share within the sector. Again, due to the markup–market share relation in our setting, this implies the average firm markup is expected to comove negatively with sector output, as summarized by [Proposition 4](#).

To evaluate this implication of the model, we implement the following reduced-form regression, in the data and in our model-simulated data:

$$(39) \quad \log(\mu_{kit}) = \alpha_i + \gamma_t + \beta_1 \log Y_{kt} + \beta_2 \log Y_{kt} \times s_{kit} + \epsilon_{it},$$

where $\log(\mu_{kit})$ is firm i sector k (log) gross markup in year t , $\log Y_{kt}$ is sector k 's (log) value added in year t , and s_{kit} is firm-level market share for firm i in sector k at year t .⁴¹ Given the specification in log levels, α_i is a firm fixed effect, which controls for time-invariant firm-level unobservables determining the average level of a firm's markup, while γ_t is a year fixed effect.⁴² In this specification, β_1 captures the average correlation between firm markups and their respective sector output, and coefficient β_2 , in the interaction term, captures heterogeneity in this relation.⁴³ For robustness, we consider a specification in first differences of (log) firm markups, $\Delta \log(\mu_{kit})$, and (log) sectoral value added, $\Delta \log Y_{kt}$ and no firm-level fixed effects. Finally, in [Online Appendix E.4](#) we consider alternative measures of sector output.

Before proceeding, note that [Hong \(2017\)](#) estimates a similar version of this regression with aggregate output Y_t in place of sectoral output Y_{kt} , using data for four large European countries. For these data, [Hong \(2017\)](#) obtains a negative β_1 and a positive β_2 estimate, concluding that (i) in the data “markups are countercyclical” and (ii) that there is “substantial heterogeneity in markup cyclicalities across firms, with small firms having significantly more countercyclical markups than large firms.”⁴⁴

[Table VI](#), columns (1) and (2) summarize the estimates of the reduced-form [regression \(39\)](#) on our French firm-level data in both levels (with firm fixed effects) and first differences of logged variables. In both cases, point estimates β_1 are negative and significant: the markup of the average firm is “countercyclical” with respect to own-sector output. Although the point estimates vary across empirical specifications, the average firm's markup behavior qualitatively aligns with our model's predictions. Furthermore, there is substantial heterogeneity in markup cyclicalities across firms. In particular, the estimates for the interaction term—in both specifications—imply that markups of firms with

41. To obtain sector value added, we sum firm-level nominal value added to the NAF five-digit level and deflate using EU-KLEMS sectoral price deflators.

42. We drop the year 1994 to have the same yearly coverage as in [Section V](#). For this reason, the number of observations is lower than what is reported in [Online Appendix Table A1](#). Including the year 1994 gives very similar results.

43. According to our model, given the parameters ε and σ , the market share suffices to determine the markup ([equation \(5\)](#)). For this reason, we estimate [equation \(39\)](#) without further controls.

44. When we consider [regression \(39\)](#) using aggregate output, Y_t , rather than sectoral output, Y_{kt} , we find the same qualitative results as in [Hong \(2017\)](#).

TABLE VI
FIRM MARKUP AND SECTOR OUTPUT

Dependent variable	Data log(μ_{kit}) (1)	Data $\Delta \log(\mu_{kit})$ (2)	Model log(μ_{kit}) (3)	Model $\Delta \log(\mu_{kit})$ (4)
Y_{kt}	−0.073 (0.008)		−0.001	
$\log Y_{kt} \times s_{kit}$	0.574 (0.044)		0.265	
$\Delta \log Y_{kt}$		−0.024 (0.009)		−0.001
$\Delta \log Y_{kt} \times s_{kit}$		0.280 (0.040)		0.247
Firm FE	Y	N	Y	N
Year FE	Y	N	Y	N
Number of observations	9,039,476	8,051,767	—	—

Notes. μ_{kit} is firm i sector k gross markup in year t , s_{kit} gives the market share of firm i in sector k , year t and $\log Y_{kt}$ sector k 's (log) value added in year t . $\Delta \log(\mu_{kit})$ is the first difference of (log) gross markup in year t for firm i sector k , s_{kit} gives the market share of firm i in sector k , year t and $\Delta \log Y_{kt}$ is the first difference of sector k (log) value added in year t . Columns (1) and (2) report empirical estimates for the FICUS-FARE (1995–2019) data. Standard errors (in parentheses) are two-way clustered at the sector $\times$ year level. Columns (3) and (4) report estimates based on model-simulated data. Log and first difference of log markup are winsorized at the 3% level.

market shares roughly above 10% (in the top 0.1% of the market share distribution) are procyclical with respect to sectoral output. However, the vast majority of firms have a countercyclical markup with sectoral output since the average firm has a very low market share (roughly 0.07%).⁴⁵

Table VI, columns (3) and (4) implement these reduced-form regressions on model-simulated data for 399,520 firms distributed across 275 sectors at the five-digit level.⁴⁶ The model is able to reproduce the qualitative patterns observed in the data. In line with Proposition 4, markups are countercyclical with respect to own-sector output for the average firm and procyclical for large firms. Furthermore, point estimates for the implied large-firm procyclicality are of the same order of magnitude in the

45. We also consider an alternative specification where sector value added is interacted with an indicator for market shares over 50%. We find a coefficient of 0.240 (0.044) on the interaction term for the log-level specification and of 0.026 (0.013) for the first-difference specification.

46. The number of firms is smaller in the simulation than in the data because our model abstracts from entry and exit and targets the yearly average number of firms in the economy over our period.

model and the data and particularly close for the first-differences specification. In [Online Appendix E.4](#), we show that these results are robust to alternative definitions of sectoral output dynamics, by considering log deviations of sector real value added from its trend (defined by either a Hodrick-Prescott or [Hamilton 2018](#) filters).

As discussed, underlying the prediction of the model for heterogeneous cyclicity of firm-level markups is the fact that in our granular environment, large firms' market shares are correlated positively with sector output, whereas small firms' market shares are countercyclical. To assess this mechanism in the data, we estimate the following regression:

$$\log(s_{kit}) = \alpha_i + \gamma_t + \beta \log Y_{kt} + \epsilon_{kit},$$

where $\log(s_{kit})$ is the (log of) market share of firm i in sector k , $\log Y_{k,t}$ is the (log of) sector k real value added, α_i is a firm-level fixed effect, and γ_t is a year fixed effect. We also consider a first-difference specification (without firm fixed effects). In either specification, β measures the relation between market share and sector value added. To assess the predicted heterogeneous behavior of firm-level market shares with respect to sector output, we implement this regression (i) on the whole sample of firms, (ii) on the subsample of firms whose average market share is lower than 50%, and (iii) on the subsample of firms whose average market share is above 50%.

[Table VII](#), columns (1) and (4) report estimates of β on the French data and on model-simulated data. Both in the data and in the model—and for level and first-difference specifications—the average firm's market share is countercyclical. Columns (2) and (5) report estimates for the subsample of firms whose market share is lower than 50%. Estimates of β are negative in the data and in the model. Columns (3) and (6) report estimates for the subsample of firms whose market share is above 50%: consistently with our argument, estimates of β are now positive in the data and in the model, although the magnitude is smaller in the data.⁴⁷ In [Online Appendix E.4](#) we confirm that these findings are robust to alternative detrending

47. In our model, changes in sectoral output are driven by independent firm-level shocks. Adding sector-level productivity or demand shifters that affect all firms symmetrically would reduce the estimate of β , bringing it more in line with our empirical findings.

TABLE VII
FIRM MARKET SHARE AND SECTOR OUTPUT

	Data (all data) (1)	Data ($\bar{s}_{kit} < 0.50$) (2)	Data ($\bar{s}_{kit} > 0.50$) (3)	Model (all data) (4)	Model ($\bar{s}_{kit} < 0.50$) (5)	Model ($\bar{s}_{kit} > 0.50$) (6)
$\log s_{kit}$						
Dependent variable						
$\log Y_{kt}$	-0.594 (0.009)	-0.595 (0.009)	0.144 (0.060)	-2.613	-2.621	0.535
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Number of observations	9,039,476	9,039,036	440	—	—	—
$\Delta \log s_{kit}$						
Dependent variable						
$\Delta \log Y_{kt}$	-0.488 (0.018)	-0.488 (0.018)	0.091 (0.037)	-2.585	-2.591	0.274
Firm FE	N	N	N	N	N	N
Year FE	N	N	N	N	N	N
Number of observations	8,251,767	8,251,340	427	—	—	—

Notes. Gives the market share of firm i in sector k , year t , and $\log Y_{kt}$ is the deviation of sector k (log) value added in year t from its mean. $\Delta \log s_{kit}$ gives the first difference of (log) market share of firm i in sector k , year t , and $\Delta \log Y_{kt}$ is the first difference of sector k (log) value added in year t . $\bar{s}_{kt}$ is the average market share of firm i in market k . Columns (1)–(3) reports empirical estimates for the FICUS-FARE (1995–2019) data. Sectors are defined at the five-digit NAF sector classification level. First differences in log market shares are winsorized at the 3% level. Standard errors (in parentheses) in the data are two-way clustered at the sector $\times$ year level. Columns (4)–(6) reports estimates based on model-simulated data.

techniques for sectoral output dynamics. Taken together, these results provide support for a key implication of our granular model with firm-level shocks. The average firm's market share and markup are countercyclical with respect to its own sector value added, whereas large firms' market share and markups are procyclical.

VI.B. Sector-Level Markup Cyclicalities with Sector Output

We now explore sector-level notions of markup cyclicalities. We first ask how sector markups covary with own-sector output. Recall that in our granular setting, sectoral business cycles are driven by large-firm dynamics and shocks to large firms induce changes in sector-level output and markups. According to [Proposition 3](#), we should expect a positive correlation between sector markup and sector output.

To assess this relationship in the model and in the data, we follow [Nekarda and Ramey \(2013\)](#) and consider the following sector-level specification:

$$(40) \quad \Delta \log \mu_{kt} = \alpha_k + \gamma_t + \beta \Delta \log Y_{kt} + \epsilon_{kt},$$

where $\Delta \log \mu_{kt}$ denotes the first difference of sector k 's (log) markup, and $\Delta \log Y_{kt}$ denotes the first difference of sector k 's (log) real value added. Sector-level markups are aggregated from firm-level estimates according to a harmonic weighted average, as indicated by the model [equation \(7\)](#).⁴⁸ We measure sector value-added in the data as in the previous section. We follow [Nekarda and Ramey \(2013\)](#) and include sector and year fixed effects to control for possibly heterogeneous trends in sector-level growth rates. For robustness, we also consider an alternative specification where we use sectoral variables in log deviations from trend (rather than first differences) where the trend is estimated following [Hamilton \(2018\)](#). Finally, in [Online Appendix E.5](#) we consider additional fixed-effect specifications for variables in levels and alternative detrending procedures.

[Nekarda and Ramey \(2013, 2\)](#) estimate a positive and significant β in U.S. sectoral data using a similar specification, concluding that “markups are generally procyclical . . . hitting troughs

48. [Nekarda and Ramey \(2013\)](#) measure sectoral markups using various measures of the inverse of the labor share at the sectoral level. We construct sector-level markups from the aggregation of firm-level markups based on [equation \(34\)](#) with material as a variable input.

TABLE VIII
SECTOR MARKUP AND SECTOR OUTPUT

Dependent variable	Data $\Delta \log \mu_{kt}$ (1)	Data $\log \hat{\mu}_{kt}$ (2)	Model $\Delta \log \mu_{kt}$ (3)	Model $\log \hat{\mu}_{kt}$ (4)
$\Delta \log Y_{kt}$	0.160 (0.040)		0.110 (0.040)	
$\log \hat{Y}_{kt}$		0.139 (0.057)		0.117 (0.035)
Sector FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Number of sectors	275	275	275	275
Number of observations	6,875	6,325	6,875	6,325

Notes. Regression of sector-level (log) change (columns (1) and (3)), and [Hamilton \(2018\)](#) trend deviation of markup (columns (2) and (4)), $\Delta \log \mu_{kt}$ and $\log \hat{\mu}_{kt}$ on sector value added $\Delta \log Y_{kt}$ and $\log \hat{Y}_{kt}$, respectively. Columns (1) and (2) reports empirical estimates for the FICUS-FARE (1995–2019) data, and standard errors (in parentheses) are clustered at the sector level. Sectors are defined at the five-digit NAF sector classification level. To construct sector-level markups the underlying firm-level inverse markups are winsorized at 3%. Columns (3) and (4) report estimates based on model-simulated data. The point estimates for these columns give the median coefficient obtained from running the reduced-form regression over 5,000 simulated samples, each of the same length (25 years) as the French data. The standard errors (in parentheses) are computed over the same simulated samples.

during recessions and reaching peaks in the middle of expansions.”

[Table VIII](#) reports estimates of β in our French data using both first-difference (column (1)) and trend-deviation specifications (column (2)). Sector markups comove positively and significantly with sector output, which is consistent with the findings in [Nekarda and Ramey \(2013\)](#) despite differences regarding the country of analysis, sample period, and the methods to estimate markups. [Online Appendix E.5](#) further confirms the robustness of this correlation to alternative empirical specifications and detrending procedures.

[Table VIII](#), columns (3) and (4) report estimates of β in model-simulated data, applying the same empirical specifications as in the French data. We report the median and standard deviation of β estimates over 5,000 samples of 25 years each. The model implies a positive correlation between sector markup and sector output, yielding point estimates that are only slightly lower than their empirical counterpart.

To further understand the previous result, recall that sector-level markups in our model are linked to sector-level concentration as measured by the HHI, a relationship we explored empirically in [Section V.B](#). Therefore, underlying the cyclicity of

TABLE IX
SECTOR CONCENTRATION AND SECTOR OUTPUT

Dependent variable	Data $\Delta \log HHI_{kt}$ (1)	Data $\log \widehat{HHI}_{kt}$ (2)	Model $\Delta \log HHI_{kt}$ (3)	Model $\log \widehat{HHI}_{kt}$ (4)
$\Delta \log Y_{kt}$	0.332 (0.067)		0.533 (0.235)	
$\log \widehat{Y}_{kt}$		0.281 (0.049)		0.726 (0.288)
Sector FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Number of sectors	275	275	275	275
Number of observations	6,875	6,325	6,875	6,325

Notes. Regression of sector-level (log) change (columns (1) and (3)), and [Hamilton \(2018\)](#) trend deviation of HHI (columns (2) and (4)) $\Delta \log HHI_{kt}$ and $\log \widehat{HHI}_{kt}$ on sector value-added $\Delta \log Y_{kt}$ and $\log \widehat{Y}_{kt}$, respectively. Columns (1) and (2) report empirical estimates for the FICUS-FARE (1995–2019) data, and standard errors (in parentheses) are clustered at the sector level. Sectors are defined at the five-digit NAF sector classification level. Columns (3) and (4) report estimates based on model-simulated data. The point estimates for these columns give the median coefficient obtained from running the reduced-form regression over 5,000 simulated samples, each of the same length (25 years) as the French data. The standard errors (in parentheses) are computed over the same simulated samples.

sector-level markups is the cyclicity of the sectoral HHI. In our granular environment, in a typical sectoral expansion a few large firms expand by increasing their market share while smaller firms lose market share, resulting in higher concentration. To assess this mechanism in the data, we estimate a similar specification to [equation \(40\)](#), with sectoral HHI rather than sectoral markup on the left side:

$$\Delta \log HHI_{kt} = \alpha_k + \gamma_t + \beta \Delta \log Y_{kt} + \epsilon_{kt}.$$

Here, $\Delta \log HHI_{kt}$ is the first difference of sector k 's (log) HHI, and $\Delta \log Y_{kt}$ denotes the first difference of sector k 's (log) output. We include sector and year fixed effects as in the markup cyclicity specification, [equation \(40\)](#). As before, we consider an alternative specification where we use log deviations from trend computed as in [Hamilton \(2018\)](#) and present further robustness exercises in [Online Appendix E.5](#).

[Table IX](#), columns (1) and (2) report estimates of β in our French data for first-difference and trend-deviation specifications. Sector concentration comoves positively and significantly with sector output. We next apply the same empirical specification to model-simulated data, and we calculate the median and standard deviation of β estimates over 5,000 samples of 25 years each. Columns (3) and (4) show positive and significant estimates of

β that are comparable in magnitude to those in the data. [Online Appendix Table A14](#) confirms the robustness of this correlation to alternative empirical specifications and detrending procedures.

VI.C. Sector-Level Markup Cyclicalities with Aggregate Output

The work by [Bils, Klenow, and Malin \(2018\)](#) explores yet another reduced-form notion of markup cyclicalities. Unlike the previous specification, which relates changes in sectoral markups and changes in sectoral output, [Bils, Klenow, and Malin \(2018\)](#) measure cyclical comovement between sectoral markup and aggregate real GDP. More recently, [Anderson, Rebelo, and Wong \(2023\)](#) explore a similar notion of cyclicalities when assessing markup dynamics in retail sectors.

To understand this form of comovement in the context of our model, note that sector markups only react to within-sector firm shocks. Over long samples, under the conditions of [Proposition 5](#), the model implies (i) positive comovement of a sector's markup with aggregate GDP and (ii) that this comovement is nevertheless weaker than that between a sector's markup and its output (see footnote 25). Over a given cyclical episode—or more generally, in small samples—the model prediction is ambiguous. A positive comovement is expected if the fluctuation in aggregate economic activity is driven by large firms in the same sector. However, aggregate output movements also reflect shocks hitting other sectors in the economy. If a sector comoves negatively with aggregate output, a negative correlation of that sector's markup with aggregate output will obtain. Overall, we should expect a weaker relationship between the average sector's markup and aggregate GDP fluctuations than between sectoral markups and sectoral output.

To explore this notion of cyclicalities, we implement the following regression:

$$(41) \quad \Delta \log \mu_{kt} = \alpha_k + \beta \Delta \log Y_t + \epsilon_{kt},$$

where $\Delta \log \mu_{kt}$ is the first difference of sector k 's log markup in year t , $\Delta \log Y_t$ is the first difference of (log) aggregate value added in year t , and α_k is a sector fixed effect that controls for sector-specific trends in markups. Sector-level markups are computed as before by taking a weighted harmonic mean of firm-level markups and aggregate value added is computed by summing firm-level value added deflated by the respective EU-KLEMS sector-level deflator. For robustness, we again consider specifications in log deviations from a [Hamilton \(2018\)](#) trend rather than

growth rates. In [Online Appendix E.5](#) we consider an alternative HP-filter detrending procedure.

[Bils, Klenow, and Malin \(2018\)](#) consider a version of this regression based on U.S. data.⁴⁹ They conclude that “the price markup is estimated to be highly countercyclical” with the possible exception of service industries, for which they find evidence favoring procyclicality. In the same vein, [Anderson, Rebelo, and Wong \(2023\)](#) study the cyclicalities of markup growth of one particular sector—U.S. retail—with respect to GDP growth. They report a positive but statistically insignificant relation, leading them to conclude that markups in retail are “roughly acyclical or mildly procyclical.”

[Table X](#), columns (1) and (2) summarize our estimates based on French data. While the point estimates are negative, the standard errors are large. The coefficient in column (1) is marginally significant (t -statistic of 2.06) while that in column (2) is insignificant (t -statistic of 1.53). As shown in [Online Appendix Tables A15](#) and [Table A3](#), both the sign and significance of this reduced-form relation are sensitive to the specific detrending choice, sample definition, and the measure of markup used.

We now explore the relation between sector-specific markups and aggregate output implied by our model. [Table X](#) presents median estimates (along with their respective standard errors) of β over 5,000 samples of 25-year length. For the baseline calibration, reported in columns (3) and (4), our model implies a positive point estimate. However, the model simulations point to considerable variation in this relation across small samples, with a point estimate that is not statistically different from zero.

As we will discuss in [Section VII](#), our model with only idiosyncratic productivity shocks understates aggregate output volatility. To match the observed volatility of aggregate output, we consider an extension with aggregate productivity shocks. Firm-level productivity is given by $Z_t \times Z_{ikt}$, where $\tilde{Z}_t$ is normally

49. [Bils, Klenow, and Malin \(2018\)](#) measure markups using intermediate input shares computed from sector-level data from KLEMS. Here, we construct sector-level markups by the aggregation of firm-level markups based on [equation \(7\)](#), and we use material as a variable input to estimate firm-level markups using [equation \(34\)](#).

TABLE X
SECTOR MARKUP AND AGGREGATE OUTPUT

Dependent variable:	Data		Model without aggr. shocks		Model with aggr. shocks	
	$\Delta \log \mu_{kt}$ (1)	$\log \hat{\mu}_{kt}$ (2)	$\Delta \log \mu_{kt}$ (3)	$\log \hat{\mu}_{kt}$ (4)	$\Delta \log \mu_{kt}$ (5)	$\log \hat{\mu}_{kt}$ (6)
$\Delta \log Y_t$	-0.239 (0.116)		0.165 (0.101)		0.008 (0.042)	
$\log \hat{Y}_t$		-0.145 (0.095)		0.169 (0.119)		0.017 (0.044)
Share negative coefficients	—	—	0.02	0.02	0.29	0.21
Sector FE	Y	Y	Y	Y	Y	Y
Number of sectors	275	275	275	275	275	275
Number of observations	6,875	6,325	6,875	6,325	6,875	6,325

Notes. Regression of sector k 's markup in year t in first differences ($\Delta \log \mu_{kt}$, in columns (1), (3), and (5)) and Hamilton (2018) trend deviation ($\log \hat{\mu}_{kt}$, in columns (2), (4), and (6)) on (log) aggregate real value added in year t in either first differences or Hamilton (2018) trend deviation ($\Delta \log Y_t$ and $\log \hat{Y}_t$, respectively). Columns (1) and (2) report empirical estimates for the FICUS-FARE (1995–2019) data. Regressions are weighted by average sectoral value added. To construct sector-level markups the underlying firm-level inverse markups are winsorized at 3%. Standard errors (in parentheses) are clustered at the sector level. Columns (3) and (4) report estimates based on model-simulated data. Point estimates for this column give the median coefficient obtained from running the reduced-form regression over 5,000 simulated samples, each of the same length (25 years) as the French data. The standard errors (in parentheses) are computed over the same simulated samples. Columns (5) and (6) report estimates based on model-simulated data with aggregate TFP shocks. Point estimates for this column are computed as for columns (3) and (4). The volatility of the serially uncorrelated aggregate TFP shocks is calibrated to match the aggregate volatility of aggregate output (either measured as a deviation from trend or a log first difference) in France. The line “Share negative coefficients” gives the share of simulations with negative estimated coefficients in regression on the model-based simulations.

distributed and independent across periods with volatility set to match the volatility of aggregate output in the data.⁵⁰

For this alternative parameterization, reported in columns (5) and (6), our model implies a point estimate that is roughly equal to zero. Of the 5,000 samples, about 20%–30% (depending on how we filter the model-generated data) display sectoral markups that are countercyclical with respect to aggregate output. Intuitively, aggregate productivity shocks enhance aggregate output volatility but do not affect the relative firm-level productivity and therefore do not affect the market share and markup distributions. It follows that aggregate shocks do not affect sector-level markups. Point estimates with aggregate shocks are therefore smaller than without aggregate productivity shocks and closer to their empirical counterparts. We conclude that the model can generate a weaker comovement between sectoral markups and aggregate output in comparison to the more robust positive relation between sectoral markups and sectoral output.

VI.D. *Robustness of Empirical Results to Alternative Samples and Markup Measures*

As explained in [Section IV.A](#), our measure of markups is constructed by combining (i) estimates of the production function at the two-digit level on a restricted sample of firms with revenue and quantity data, referred to as the estimation sample, and (ii) expenditure shares on materials from a larger sample of firms, referred to as the baseline sample. This procedure allows us to construct firm-level markups for about 9.4 million firm-year observations from 1994 to 2019. In this section, we discuss the sensitivity of our empirical results to using the restricted estimation sample or alternative measures of markups. We provide additional information and robustness exercises in [Online Appendix C](#).

We begin by recalculating our results in the smaller estimation sample, which contains 220,733 observations over the shorter period 2009–2019. The results are collected in [Online Appendix Table A3](#), column (7) and can be compared with our baseline estimates in column (1). The qualitative conclusions remain similar, though with reduced statistical significance. This reflects both a smaller sample size—fewer time periods and firms—and an un-

50. We set the standard deviation of $\log \tilde{Z}_t$ to 2.20% (respectively, 2.04%) for the specification in first differences (respectively, in deviation from trend).

derrepresentation of small firms in the population. By extending the sample of firms beyond those with quantity data, our baseline sample addresses these two issues.

We calculate markups using output elasticities estimated using revenue rather than quantity data. Revenue-based markups are more widely used in the literature than quantity-based markups because revenue data are more readily available but are prone to the biases discussed in [Bond et al. \(2021\)](#) and [De Ridder, Grassi, and Morzenti \(2024\)](#). [Anderson, Rebelo, and Wong \(2023\)](#) show sizable differences in markup levels estimated using quantity or revenues data for a large U.S. and Canadian retailer. We obtain in our data similar differences in the average level of quantity and revenue-based markups to those reported in [Anderson, Rebelo, and Wong \(2023\)](#), as shown in [Online Appendix Table A2](#). Nevertheless, when we reestimate our central empirical specifications using revenue-based markup (see [Online Appendix Table A3](#), column (5)) the results are qualitatively similar to our baseline, with only a few exceptions: the relation between sector markups and concentration retains the baseline sign but loses significance, while the relation between sectoral markups and aggregate output gains significance albeit with point estimates that are now closer to zero. The fact that many of the patterns on markup cyclicalities do not change much when using revenue- or quantity-based markups is consistent with results in [De Ridder, Grassi, and Morzenti \(2024\)](#). While revenue-based markups levels are biased, [De Ridder, Grassi, and Morzenti \(2024\)](#) provide conditions and quantitative examples under which they are positively correlated (across firm or/and over time) with quantity-based markups.

In the same vein, in [Online Appendix C.1](#) we run our baseline specifications using accounting markups computed with the Lerner index, without involving any production function estimation. While immediate to compute, these accounting-based measures only recover markups if firms operate a constant returns to scale technology and costs are correctly accounted for. The results are displayed in [Online Appendix Table A3](#), column (2). Results are qualitatively similar to our baseline.

[Online Appendix Table A3](#) also shows that our empirical results are largely robust to individual perturbations of our benchmark procedure, such as the treatment of outliers, multiproduct firms, and time coverage.

TABLE XI
AGGREGATE MARKUP AND AGGREGATE OUTPUT

	Data			Model without aggr. shocks			Model with aggr. shocks		
	(1)			(2)			(3)		
	σ_x	$\frac{\sigma_x}{\sigma_Y}$	$\rho(x, Y)$	σ_x	$\frac{\sigma_x}{\sigma_Y}$	$\rho(x, Y)$	σ_x	$\frac{\sigma_x}{\sigma_Y}$	$\rho(x, Y)$
$\log \widehat{Y}_t$	3.16	1	1	0.83	1	1	3.16	1	1
$\log \widehat{\mu}_t$	1.27	0.40	0.03	0.30	0.36	0.91	0.30	0.09	0.29
$\Delta \log Y_t$	3.28	1	1	0.72	1	1	3.28	1	1
$\Delta \log \mu_t$	1.63	0.50	0.06	0.26	0.36	0.91	0.26	0.08	0.27

Notes. The table reports standard deviations, σ_x , relative standard deviations, $\frac{\sigma_x}{\sigma_Y}$, and time-series correlations, $\rho(x, Y)$, for deviations from trend computed as in [Hamilton \(2018\)](#) of (log) aggregate output $\log \widehat{Y}_t$ and (log) aggregate markup $\log \widehat{\mu}_t$, and, for the log first difference of aggregate output $\Delta \log Y_t$ and aggregate markup $\Delta \log \mu_t$. Column (1) reports empirical estimates for the FICUS-FARE (1995–2019) data. Column (2) reports the median over 5,000 simulated samples, each of 25 years. Column (3) reports the average over 5,000 simulated samples of 25 years from a model with aggregate TFP shocks. The volatility of the serially uncorrelated aggregate TFP shocks is calibrated to match the aggregate volatility of aggregate output (either measured as a deviation from trend or a log first difference) in France.

VII. FLUCTUATIONS IN AGGREGATE MARKUP AND OUTPUT

In this final section, we turn our attention to the volatility and cyclicity of aggregate markup and output fluctuations in the data and in the quantitative model. We consider our model with only idiosyncratic firm-level shocks that follow the Markov process introduced above. Then we introduce aggregate productivity shocks to fully account for aggregate output volatility in our data.

Using the FICUS-FARE data, we construct aggregate markups, μ_t , as a weighted harmonic mean of firm-level markups, and aggregate GDP, Y_t , as described in [Section VI.C](#). We detrend these variables using the [Hamilton \(2018\)](#) filter. Using our calibrated model, we simulate 5,000 samples of 25-year firm-level histories. We implement the same procedure to construct detrended time-series of model-simulated aggregate output and markups. For robustness, we also consider a first-differences specification. [Table XI](#) presents data- and model-based estimates of the correlation and standard deviation of aggregate output and markups.

We first consider aggregate markup cyclicity. Recall from [expression \(33\)](#) that our model implies a positive comovement between aggregate output and aggregate markups unless larger sectors have lower markups or, for finite samples, if a particular expansionary episode is driven by a sector with a sufficiently low

markup, in which case negative comovement may obtain. That is, whereas according to our model we should observe positive comovement over sufficiently long samples, in any given short sample comovement may be absent or negative depending on the sectors driving the aggregate fluctuations.

In [Table XI](#), we can see that in the data and in the model the correlation between the aggregate markup and aggregate output is positive. Our model predicts, however, much higher correlation than that observed in the data: the correlation is at most 0.06 in the data and 0.91 (computed as the median correlation across shock realizations) in the model.⁵¹

Next, we examine the magnitude of aggregate fluctuations in output and markups implied by our model. The literature quantifying the granular origin of business cycles (see [Gabaix 2011](#); [Carvalho and Grassi 2019](#)) has largely abstracted from considerations of oligopolistic competition and incomplete pass-through. Recall from our analytic results in [Section III.C](#) that incomplete pass-through weakens the response of aggregate output to firm-level shocks relative to a specification of the model with heterogeneous but constant markups.

[Table XI](#) shows that for the detrended specification, the standard deviation of aggregate output is 3.16% in our French data and 0.83% in our model (median across samples). That is, the volatility of aggregate output in our purely granular model is 26% of the volatility in the data (we obtain very similar results if we calculate volatilities using first differences). This is only slightly smaller than the comparable number in [Carvalho and Grassi \(2019\)](#) who report, in their perfectly competitive granular environment, a volatility of model GDP relative to (U.S.) data of 30%. How large are granular movements in aggregate markups? In the data, the relative volatility of the aggregate markup to aggregate output ranges from 40% to 50%, depending on the detrending method. Our calibrated model generates a relative volatility of 36% (median across samples).

51. Our model predicts large variation in the correlation coefficient and in the relative volatility of aggregate markups and output across small samples, depending on which sectors are driving aggregate dynamics and the relative levels of their markups. To see this variation at play, [Online Appendix Figure A1](#) plots the histogram of correlation coefficients $\rho(\Delta \log \mu_t, \Delta \log Y_t)$ and relative standard deviations $\frac{\sigma(\Delta \log \mu_t)}{\sigma(\Delta \log Y_t)}$ across our 5,000, 25-year samples.

Although our model with firm-level shocks generates nonnegligible fluctuations in aggregate output and markups, it only accounts for a fraction of aggregate fluctuations in the data. Moreover, as we discussed, the correlation of markups and output is much higher than that in the data. In what follows we show that if we superimpose on our calibrated model aggregate productivity shocks—to match aggregate output volatility in the data—the procyclicality of markups is much lower and closer to the data.

As described in the previous section, we assume that firm-level productivity is given by $\tilde{Z}_t \times Z_{ikt}$, where $\tilde{Z}_t$ is normally distributed and independent across periods. We choose the standard deviation of $\tilde{Z}_t$ to match the volatility of aggregate output in the data. Table XI, column (3) shows the implied business cycle moments for the median 25-year sample. As discussed in Section II, aggregate shocks do not affect firm market shares and markups, hence the volatility of aggregate markups is unchanged relative to the model with only firm-level shocks. Because movements in output driven by aggregate productivity shocks are uncorrelated with markups, the correlation between the aggregate markup and output falls to 0.27. In 16% of our 25-year samples, aggregate markups are countercyclical.⁵²

1. *Role of Changes in Firm-Level Markups for Aggregate Results.* The within/between decomposition in Section V demonstrates the importance of changes in firm-level markups to account for changes in sectoral markups in the model and data, as discussed in Section III. However, this does not imply that movements in aggregate output and markups would be very different if firm-level markups were heterogeneous but fixed over time.

To examine this counterfactual, we use the first-order approximation expressions derived in Section III. In Online Appendix A.6, we provide expressions for correlations and volatilities under variable markups versus constant markups, given market shares and markups in the initial equilibrium. Because in our model the distribution of firms by sector changes every

52. We also considered second-moment shocks to firm-level productivity as in Bloom et al. (2018). An increase in the dispersion of firm-level productivity shocks reallocates market shares toward large firms, increasing the aggregate markup, but also raises aggregate output (Oi-Hartman-Abel effect). That is, in our model second-moment shocks increase the correlation between the aggregate markup and output.

period, we consider 1,000 independent samples drawn from the equilibrium in our quantitative model.⁵³

Consider first movements in aggregate output. We compare the standard deviation of aggregate output under variable markups with that under heterogeneous but constant markups, given the same initial firm-level expenditure shares and markups and assuming the same volatility of firm-level shocks.⁵⁴ For the median sample, the standard deviation of aggregate output under variable markups is 0.87 times that under heterogeneous but constant markups (the 95% confidence interval calculated across samples is 0.82–0.97). As explained in [Section III](#), incomplete pass-through (given pass-through rates that are decreasing in size) reduces aggregate output volatility in a similar way that a decline in firm concentration does.⁵⁵

Consider movements in aggregate markups. For the median sample, their standard deviation under variable markups

53. The magnitudes of correlations and ratios of standard deviations based on the first-order approximations are remarkably close to those in our quantitative nonlinear results. For the median sample, the standard deviation of the aggregate markup relative to output is 0.42 (versus 0.36 in our quantitative nonlinear results) and the correlation between the aggregate markup and output is 0.87 (versus 0.91 in our quantitative nonlinear results).

54. Market shares of large firms are less volatile under variable markups than under constant markups. One could compare aggregate volatilities under these two specifications after adjusting the size of firm-level shocks to keep the same average volatility of market shares (which, recall, is a target in our baseline calibration). If we match an unweighted average of these market share volatilities, our results remain roughly unchanged. If we target a weighted average of these market share volatilities, aggregate volatility is slightly higher under variable markups. In all cases, variable markups have a limited effect on reducing aggregate output volatility.

55. Whereas variable markups reduce the volatility of aggregate output, markup heterogeneity per se contributes to higher aggregate volatility. By [equation \(30\)](#), markup heterogeneity under constant markups does not affect output changes with linear disutility of labor ($f \rightarrow \infty$). However, with finite labor disutility, reallocation of economic activity across heterogeneous markup firms is an additional source of output fluctuations, as studied in [Baqae and Farhi \(2020\)](#). In our model, the median standard deviation under heterogeneous and constant markups is 1.18 times that under homogeneous and constant markups (the 95% confidence interval is 1.13–1.22). Combining both results, the standard deviation under variable and heterogeneous markups is 1.02 times that under homogeneous and constant markups (the 95% confidence interval is 0.99–1.14). That is, output volatility under variable markups is only slightly higher than under constant and homogeneous markups.

is 1.08 times that under heterogeneous but constant markups (the 95% confidence interval is 1.00–1.18). The median volatility of aggregate markups relative to output is 0.42 under variable markups and 0.34 under heterogeneous but constant markups. The median correlation between markups and output is 0.87 under variable markups and 0.92 under constant markups (the 95% confidence interval for the difference in correlations is [0,0.07]).

Overall, the magnitude and cyclicity of aggregate markups in our model are not substantially different when we counterfactually fix markups at their initial, heterogeneous level. Of course, rather than exogenously fixing markups, our model provides a unified theory of markup (level) heterogeneity across firms and endogenous markup changes, which is consistent with a number of observations about markup changes in the data.

VIII. CONCLUSION

We examine markup cyclicity through the lens of a simple oligopolistic macroeconomic model with rich implications for the behavior of markups at the firm, sector, and aggregate levels. Working with administrative firm data for France, we show the model can reproduce qualitatively, and many times quantitatively, an array of markup-related empirical moments at various levels of disaggregation. In our framework and measure of markups, we can reconcile seemingly conflicting variants of “markup cyclicity” that have been considered in the literature. Finally, our granular oligopolistic setting produces nonnegligible aggregate fluctuations in output and markups.

One obvious route for future work is to superimpose in our model alternative shocks and frictions. Along this line, prime candidates would be to consider price setting and customer accumulation frictions (see [Gilchrist et al. 2017](#); [Hong 2017](#); [Afrouzi and Caloi 2024](#)), as well as aggregate monetary and financial shocks. Relatedly, we have focused on static, intratemporal markup decisions in which movements in markups are the result of changes in the shape of the demand curve in response to firm-level shocks. These forces would remain relevant even if one were to extend the model to allow for richer intertemporal dynamics that result in more complex dynamic markup strategies (see [Rotemberg and Saloner 1986](#)). Bringing the resulting firm, sector, and aggregate dynamics to data—and comparing them against the forces in our

static benchmark—would render possible an assessment of the empirical merits of this more general approach.

Finally, extensions to more realistic and richer product and market structures would allow us to more accurately map model objects to the increasingly detailed micro data available to researchers. Such extensions include multiproduct firms, interlinked through intermediate inputs, with some firms competing only locally in spatially segmented (product and factor) markets and others doing so nationwide or internationally.

SUPPLEMENTARY MATERIAL

An Online Appendix for this article can be found at *The Quarterly Journal of Economics* online.

DATA AVAILABILITY

The data underlying this article are available in the Harvard Dataverse, <https://doi.org/10.7910/DVN/UKMYBQ> (Burstein, Carvalho, and Grassi 2025).

UNIVERSITY CALIFORNIA, LOS ANGELES, AND NATIONAL BUREAU OF ECONOMIC RESEARCH, UNITED STATES

UNIVERSITY OF CAMBRIDGE AND CENTER FOR ECONOMIC POLICY AND RESEARCH, UNITED KINGDOM

BOCCONI UNIVERSITY AND INNOCENZO GASPARINI INSTITUTE FOR ECONOMIC RESEARCH, ITALY; OBSERVATOIRE FRANÇAIS DES CONJONCTURES ÉCONOMIQUES, FRANCE; AND CENTER FOR ECONOMIC POLICY AND RESEARCH, UNITED KINGDOM

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