Rising Markups, Rising Prices?

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I. Introduction

The rise in markups and market power documented by De Loecker, Eeckhout and Unger (2020) ["DLEU"] represents one of the most important recent empirical findings in economics, and has spawned a great deal of related research. Some of this new research probes the methodologies and results of DLEU.[1] Other recent work examines the evolution of market power in specific industries over long time horizons.[2]

Our starting point is the observation of Syverson (2019) that, for markups defined as price over marginal costs ($\mu \equiv P/MC$), an approximation provides:

$$\Delta P \approx \Delta \mu + \Delta MC \tag{1}$$

Therefore, increases in markups should yield increases in prices unless they are offset by marginal costs changes. In this article, we explore this empirically and assess whether the rising markups estimated by DLEU at the firm-level correlate with rising prices in the corresponding industry.

The question goes to the core of the policy agenda surrounding market power in the United States. Rising markups could be due to weakening competitive pressure that enables higher prices and a transfer of surplus from consumers to firms. Alternatively, or in addition, they could reflect changing production technologies that lower marginal costs (and possibly raise fixed costs) paired with an imperfect pass-through of marginal costs to prices.

We match the firm-level markup changes of DLEU to the price changes that arise in the firms' industry codes, obtained from the Bureau of Labor Statistics (BLS). We then examine whether firms that exhibit greater markup growth are in industries that exhibit greater price increases. We make this comparison over 1980-2018, a period over which DLEU find that average markups increase significantly. We also explore 2018:Q1-2022:Q3 in order to address recent concerns that market power has been an important driver of inflation.

Our exercise does not provide empirical support for a strong correlation between markup and price changes. This does not necessarily imply no such correlation exists because our analysis is subject to many caveats. We take as given the DLEU approach to markup estimation and the industry codes assigned by Compustat, thus any critiques of the DLEU approach are applicable here (Bond et al. 2021). The markup estimates we obtain are limited to publicly-traded firms, whereas the price indices of the BLS are intended to reflect the contributions of all domestic producers. Furthermore, price indices are not available for all industry codes listed by Compustat.

Therefore, our interpretation is that the results do not support a hypothesis that the increase in the DLEU markups is driven primarily by reductions in competition, keeping in mind that a "false negative" is possible.

II. Data and Methodology

DLEU recover markups using what is now known as the *production approach.* Consider a set of heterogeneous firms, $i = 1, \ldots, N$, that produce output in period t according to $Q_{it} = f(\Omega_{it}, V_{it}, K_{it})$, where Ω_{it} is a Hicks-neutral productivity term, V_{it}

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[1] A complete review of this literature is beyond our scope, but among the relevant articles are Bond et al. (2021), Foster, Haltiwanger and Tuttle (2022), and De Ridder, Grasse and Morzenti (2022).

[2] See Ganapati (2021), Grieco, Murry and Yurukoglu (2021), Brand (2021), Döpper et al. (2022), and Miller et al. (2022). We return to this literature in Section IV.

is a variable input that can be adjusted frictionlessly, and K_{it} is the capital stock. Under certain assumptions, the first order condition for cost minimization with respect to the variable input can be manipulated to obtain an expression for markups:

$$\mu_{it} \equiv \frac{P_{it}}{MC_{it}} = \theta^{v}_{it} \frac{P_{it}Q_{it}}{P^{V}_{it}V_{it}} \tag{2}$$

where μ_{it} is the markup, θ^{v}_{it} is the elasticity of output with respect to the variable input, P^{V}_{it} is the price of the variable input, and V_{it} is the quantity of the variable input. Thus, the markup is identified from the output elasticity, downstream revenue, and expenditures on the variable input.

Following DLEU, we obtain annual data from Compustat on the revenue and cost of goods sold for publicly-traded firms for the period from 1955-2021 (and quarterly data from 2018:Q1 to 2022:Q3). We use the replication code from DLEU to reconstruct the output elasticities and markups. This provides the nearly exact replication of the DLEU markups shown in Figure 1. We extend our estimated markups by holding estimated output elasticities fixed at the final values (from 2016) in DLEU.

We match each firm to the Producer Price Index (PPI) of the BLS. The PPI measures the average change over time in the prices of domestic producers, and can be obtained for many NAICS codes. For most of our analyses, we deflate the PPI using the Consumer Price Index (CPI) so that changes are relative to those in the overall economy.[3] We rely on the NAICS code assigned to each firm by Compustat to match firms to the PPI. For most firms, a 6-digit code is available. If PPI data are unavailable for the NAICS code assigned by Compustat then we discard the observation. We observe that the assigned NAICS codes do not change over time. Finally, we drop firms that appear for fewer than five years in Compustat to generate the results discussed in the next section.

Focusing on 1980-2018, our matched data set includes 7.794 firms that represent 50% of the firms and 59.3% of the revenue in Compustat, among firms that appear for five or more years. The average matched firm is in the sample for 12.9 years. Coverage tends to be somewhat better in the 2018:Q1-2022:Q3 quarterly data set.

Figure 1 plots the sales-weighted average markup estimates over 1955-2021, using the annual data. We show the DLEU markups, our replication of those markups, and our replication for firms that match PPI data. While the average markups rise in each case, the trend is somewhat more pronounced in the matched data set.

For each firm in the matched samples, we compute the percentage change in the markup and the percentage change in the (deflated) corresponding PPI. We annualize the percentage changes by taking the geometric mean.[4] Each observation is a firm, but not all firms are observed in all years. Thus, if a firm appears over 1995-2014, then we calculate its (average) markup and PPI growth rate based on the markup and (deflated) PPI values in 1995 and 2014.

III. Results

Figure 2 presents scatter plots in which the vertical axes are the (average) percentage change in PPIs and the horizontal axes are the (average) percentage change in markups. The left panel is for the 1980-2018 matched sample and the right panel is for the 2018:Q1-2022:Q3 matched sample. Each dot corresponds to one firm. The line of best fit is estimated with weighted least squares, with weights based on CPI-adjusted sales for the period closest to 2018 (left panel) or 2018:Q1 (right panel).

The scatter plots do not reveal a strong correlation between markup and price changes during the sample periods. The lines of best fit are flat or nearly flat and the R^2 values are 0.0005 for 1980-2018 and 0.0002 for 2018:Q1-2022:Q3.

[3] We use the CPI for All Urban Consumers: All Items in U.S. City Average (CPIAUCSL). We obtain nearly identical results if we don't deflate.

[4] This is sometimes referred to as the compound average growth rate (CAGR). We get similar results if we don't annualize the percentage change, or if we take the arithmetic rather than geometric averages.

Figure 1. : Rising Markup Estimates, 1955-2021

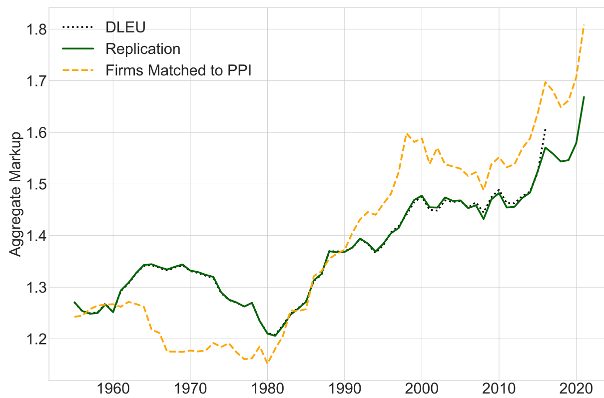
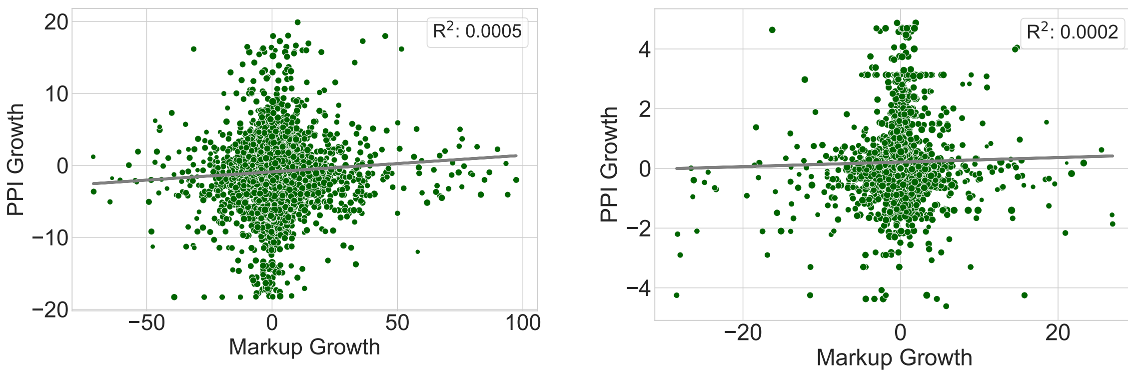


Figure 2. : Annualized Changes in Markups and Prices

(a) 1980-2018 (b) 2018:Q1-2022:Q3



Notes: The figure shows the PPI CAGR (vertical axis) and markup CAGR (horizontal axis) for firms in the matched samples. The line of best fit is estimated with weighted least squares, using CPI-adjusted sales for the period closest to 2018 (left panel) or 2018:Q1 (right panel). We exclude 30 firms (left panel) and 54 firms (right panel) with PPI or markup growth outside the range of the axes.

Table 1 provides details on the regression (weighted by deflated COGS) of PPI growth on markup growth for the full sample, on an analogous regression with category fixed effects, and on subsample regressions for each category in which we observe at least 30 matched firms. Panel A uses the 1980-2018 matched sample and Panel B uses the 2018:Q1-2022:Q3 matched sample. The coefficients provide the percentage point change in PPI growth due to a one percentage point change in markup growth.

For the 1980-2018 matched sample, we obtain an R^2 above 0.10 only for Finance and Insurance ($R^2 = 0.2376$) and for Retail Trade ($R^2 = 0.3187$). In both cases, the point estimate summarizing the correlation between markup and PPI changes is negative and statistically significant. More often, coefficients are small and statistically insignificant, and the R^2 values are near zero.

Similar results obtain with the 2018:Q1-2022:Q3 matched sample. The R^2 is above 0.10 only for Finance and Insurance ($R^2 = 0.4921$) and for Health Care and Social Assistance ($R^2 = 0.3551$), where the coefficient indicates a negative correlation between markup and PPI changes. More statistical significance is obtained than in the

Table 1—: Regression Results

Panel A: 1980-2018					
Industry	$\hat{\beta}$	SE	R^2	Obs	% Coverage
All sectors	0.03	0.01	0.00	7764	59
All sectors (with Category Fixed Effects)	0.00	0.01	0.00	7764	59
Accommodation and Food Services	-0.02	0.04	0.01	44	20
Administrative, Support, Waste Management	-0.01	0.01	0.04	38	17
Finance and Insurance	-0.34	0.06	0.24	96	60
Health Care and Social Assistance	-0.05	0.05	0.01	106	26
Information	0.00	0.02	0.00	1127	58
Manufacturing	0.02	0.03	0.00	4788	74
Mining, Quarrying, and Oil and Gas Extraction	0.09	0.02	0.03	866	73
Professional, Scientific, and Technical Services	0.03	0.04	0.01	59	11
Real Estate and Rental and Leasing	0.02	0.05	0.00	127	50
Retail Trade	-0.60	0.06	0.32	197	21
Transportation and Warehousing	-0.10	0.05	0.01	244	67
Utilities	-0.07	0.11	0.01	33	39
Panel B: 2018Q1-2022Q3					
Industry	$\hat{\beta}$	SE	R^2	Obs	% Coverage
All sectors	0.02	0.01	0.00	3161	70
All sectors (with Category Fixed Effects)	0.04	0.01	0.01	3161	70
Finance and Insurance	-0.10	0.01	0.49	57	77
Health Care and Social Assistance	-0.41	0.09	0.36	44	50
Information	-0.02	0.01	0.01	554	81
Manufacturing	0.35	0.03	0.07	1768	91
Mining, Quarrying, and Oil and Gas Extraction	0.10	0.05	0.02	291	77
Real Estate and Rental and Leasing	-0.00	0.04	0.00	80	61
Retail Trade	-0.00	0.01	0.00	121	25
Transportation and Warehousing	0.19	0.09	0.03	133	78

Notes: The table summarizes the results of weighted least squares regressions. An observation is a firm. The dependent variable is the PPI CAGR and the independent variable is the markup CAGR. Weights are by the CPI-adjusted COGS nearest to 2018 in Panel A and by the CPI-adjusted COGS nearest to 2018:Q1 in Panel B. Percentage coverage is the share of revenue among all firms in Compustat with the same 2-digit NAICS code. Most categories have a single 2-Digit NAICS code. The exceptions are Manufacturing (NAICS codes: 31-33), Retail Trade (NAICS codes: 44-45), and Transportation and Warehousing (NAICS codes: 48-49). We exclude 30 firms (Panel A) and 54 firms (Panel B) with PPI or markup growth outside the range of the axes of Figure 2. This truncation does not drive the results.

1980-2018 sample, but the signs of coefficients are mixed and most R^2 values again are small or near zero.

IV. Discussion

One explanation building on (1) is that if price changes are not explained by markup changes, then they must be explained by cost changes. If markups have been rising more quickly than prices in the aggregate, this would imply cost savings are not being fully passed on to consumers. Brand (2021) and Döpper et al. (2022) find support for this explanation in consumer packaged goods, where demand has become less elastic while price growth has been modest.

A second explanation, proposed by Syverson (2019), is that if cost of goods is more similar to average costs than marginal costs, we need to also adjust for the scale elasticity $\frac{AC}{MC}$:

$$\mu \equiv \frac{P}{MC} = \frac{P}{AC} \times \frac{AC}{MC} \tag{3}$$

Changes in scale elasticities may be hard to measure economy-wide, but industry-specific studies may provide a clearer picture regarding how firms trade higher fixed costs off against lower marginal costs.

In wholesaling, Ganapati (2021) finds that innovations in information technology increased scale economies and resulted in better service quality, lower marginal costs, higher markups, and net benefits for consumers. For cement, Miller et al. (2022) find that precalciner kilns raised fixed cost and lowered marginal cost. This increased market power as some plants closed, with prices being flat over time. A different pattern arises with steel, where Collard-Wexler and De Loecker (2015) show that minimills allowed for economical production at much lower fixed costs, which facilitated entry and reduced markups over marginal cost.

A third explanation is that the NAICS classification is not sufficient to match corresponding price changes to the estimated markup changes. Many firms produce multiple products across multiple categories. An indirect way to see if our (lack of) results represent a "false negative" would be to see if cost changes track price changes more closely than markup changes. Matching input cost data from I-O tables would represent a significant but worthwhile effort for future research.

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