Cost-Price Relationships in a Concentrated Economy*

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Abstract

We use local projections with granular instrumental variables to estimate the pass-through of costs into prices and how it is affected by industry concentration. On average, we find that prices increase above trend growth for three quarters after an exogenous cost shock, accompanied by a decline in output, with an estimated pass-through of 0.7. The price response to shocks becomes about 27 percent larger when there is an increase in concentration similar to the one observed since the beginning of this century. However, this differential effect depending on concentration is entirely driven by a higher pass-through of positive cost shocks. Consistent with market power, margins decrease less in more concentrated industries after cost increases. Within industry, margins of industry leaders are not squeezed in response to positive cost shocks, unlike those of followers, while negative shocks increase margins for all firms. Our findings shed light on the post-COVID inflationary pressures and the linkages between inflation dynamics and rising market concentration.

Keywords: Cost-Price Pass-Through, Industry Concentration, Inflation, Supply Shock Identification
JEL Codes: E30, E31, L11, L16

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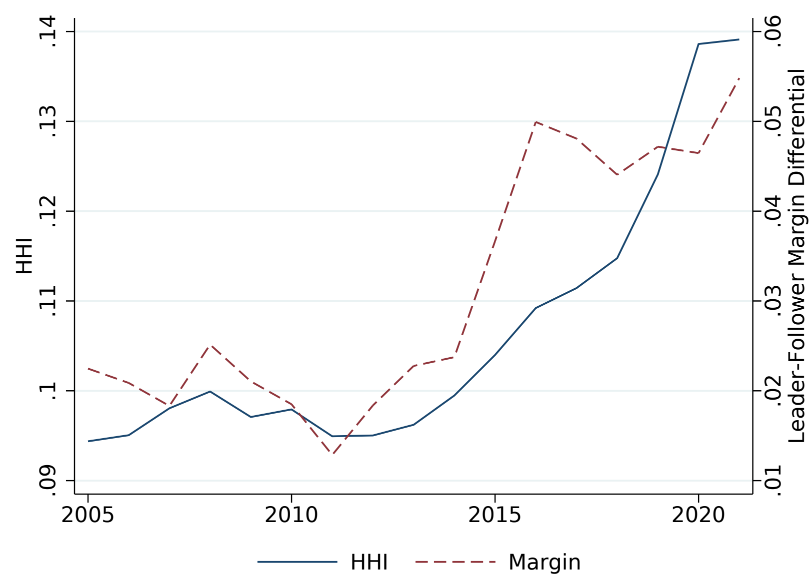
Introduction

One of the stark economic trends in the US economy is the rise in industry concentration during the past few decades (e.g., Gutiérrez and Philippon, 2017; Grullon et al., 2019). Based on the Compustat data that we use in this study, Figure 1 shows that industry concentration increased by about 50 percent from 2005 to 2020. During the same period, profit margins of industry leaders trended upward relative to industry peers, consistent with Covarrubias et al. (2020) and others who show that the increase in concentration is associated with decreasing competition and increasing barriers to entry.[1]

Figure 1: Trend in Industry Concentration



Note: Sales-weighted average industry concentration measured by sales Herfindahl index (HHI) and sales-weighted average within-industry margin differential between industry leaders and followers. Firms related to the Utilities, Financial Services, Public Administration, Gasoline Stations, and Postal Service industries, as well as industries with only one firm at any point in our sample, are dropped. For full details on definitions and data cuts, see the data section. Source: Compustat, authors' calculations.

A growing line of research studies the impact of the increase in concentration and market power on a variety of macroeconomic outcomes, including the labor income share, productivity, and economic growth, among others (e.g., Gutiérrez and Philippon, 2017; Syverson, 2019; De Loecker et al., 2020). In the context of recent supply shocks—e.g., supply chain disrup-

[1]Covarrubias et al. (2020) results are robust to the inclusion of foreign firms. Pellegrino (2019) finds the same increase in concentration and market power using a network model that takes into account the degree of product differentiation among producers, and that the results are robust to the inclusion of private and foreign firms. We also verify similar trends in concentration using the full Census data, see Appendix Figure B.1.

tions, commodity price shocks, and a tight labor market—and related inflationary pressure, both academics and policy makers argued fiercely about the potential role of concentration and market power on the pass-through of costs.[2] While several recent papers have explored the theoretical links between concentration and aggregate price dynamics, especially the pass-through of shocks, empirical evidence on this important question is limited to date.[3]

In this paper, we study how market concentration changes the pass-through of cost shocks into prices, which arguably is a key statistic for understanding the transmission of shocks in the economy (e.g., Gopinath and Itskhoki, 2011; Weyl and Fabinger, 2013). Our main findings can be summarized as follows: (i) cost shocks cause prices to increase above trend growth during the subsequent 3 quarters, (ii) the pass-through is 27 percent larger in more concentrated industries, and, last but not least, (iii) these dynamics are mostly driven by shocks that result in cost increases, while negative cost shocks have practically no differential effect on prices depending on industry concentration. We also find that firm-level profit margins decrease less in more concentrated industries and for industry leaders as a result of positive cost shocks.

Our empirical strategy exploits industry-level data on producer prices and real output from the Bureau of Labor Statistics (BLS) in addition to firm-level data on sales and costs from Compustat.[4] Based on data from 2005 through 2019, we estimate the impulse response functions of prices, output, and other key variables to identified cost shocks using local projections (Jordà, 2005). For identification of exogenous variation in aggregate cost measures, we leverage the granular instrumental variable (GIV) method recently developed by Gabaix and Koijen (2020). This approach builds on two key assumptions. First, granular firm-level data allow identification of idiosyncratic cost shocks, that is, changes in cost that are exogenous to the overall evolution of the economy (or industry) and specific to a given firm. Second, due to the granularity of the firm-size distribution—a few large firms account for a large share of the total economic activity in a given industry—these arguably idiosyncratic cost changes identify exogenous variation in the aggregate cost measure changes for a given industry.

We show the validity of the GIV approach for our study by meeting two requirements. First, we isolate idiosyncratic cost shocks at the firm level as residuals from saturated regres-

[2]See for example, `https://voxeu.org/article/inflation-market-power-and-price-controls-igm-forum-survey` and the references therein.

[3]For instance, Wang and Werning (2020) focus on the relationship between market structure and the transmission of monetary policy shocks to prices. As discussed below, several papers in the empirical IO literature study the cost pass-through for individual firms or single markets. Our paper looks at a broad set of industries to estimate macro effects.

[4]We use producer prices mainly because of data availability. However, the effect of market concentration on prices is also most relevant for wholesale prices (Gopinath and Itskhoki, 2011).

sion models, including industry*time fixed effects and a rich set of firm controls to purge demand factors. We verify that the firm-level residuals represent true idiosyncrasies, exogenous to the evolution of aggregate industry costs, by reviewing public reports filed with the U.S. Securities and Exchange Commission (SEC) and other sources.[5] Second, we show that, because of the skewed firm-size distribution, the aggregated identified firm-level cost residuals are relevant instruments for aggregate industry-level cost changes, as first-stage F-statistics are large and influence aggregate costs.

Using these identified cost shocks, we first estimate the average pass-through to prices across industries using local projections. In all specifications, we control for four lags of the outcome variable (prices), industry-specific intercepts, and deterministic trends, such that the response coefficients represent percentage deviations from local (pre-shock) trend growth. Our findings show that cost shocks cause an economically and statistically significant increase in prices (relative to trend) that lasts as long as three quarters after impact.[6] We also find that (endogenous) costs increase above trend growth for about three quarters after the shock. The implied price elasticities with respect to costs suggest that a 1% increase in operational expenses increases prices, on average, by about 0.7 percent one quarter ahead.[7] Consistent with a supply shock, the increase in prices is accompanied by a significant drop in real output. In contrast, least-square regressions of prices and output on *endogenous* cost measures lead to attenuated estimates close to 0, highlighting the importance of using exogenous variation in costs for identification. As a robustness exercise, we provide additional results using an alternative measure to the GIV-based supply shock measure. Results are qualitatively similar when we measure the cost shock with data on supply chain disruptions and exposure to imported inputs at the industry level, lending additional credibility to our analysis.

Crucially, we find that the pass-through of cost shocks to prices is stronger as industry concentration increases. For identification of the differential effect, we exploit changes in concentration *within* industry, which, as Hsieh and Rossi-Hansberg (2019) document, are the main source of the aggregate increase in concentration. We achieve this by altering our

[5]For example, as we discuss below, the identified idiosyncratic cost changes may be related to revaluation of inventory or implementation of firm-specific cost savings plans.

[6]In this paper, we use accounting data, which are not constructed to measure economic concepts such as marginal costs. There are primarily two types of costs: (1) Cost of Goods Sold and (2) Selling, General, and Administrative expenses. There are arguably variable and fixed cost components in both. In our baseline analysis, we use Operating Expenses—the sum of the two categories—as our cost measure. Given considerable identification challenges, we do not distinguish between variable costs and fixed costs but instead focus on replicating our results using different cost measures. We find similar results using Cost of Goods Sold only (as in De Loecker et al., 2020).

[7]The empirical pass-through literature, exploiting shocks to specific inputs and/or specific industries, has found estimates well bellow one (e.g., Nakamura and Zerom, 2010), close to one (e.g., Fabra and Reguant, 2014), and above one (e.g., Miller et al., 2017). Our estimates suggest that, for an industry-wide shock to all operating expenses and industries, we cannot reject a complete pass-through one period ahead.

local projection models to (i) allow for industry-specific slope coefficients on the cost shock as well as (ii) include an interaction term between the cost shock and the HHI, while also accounting for four lags of the HHI and the interaction term. Our estimates of the interaction term are highly significant and robust to different measures of industry concentration. The economic significance of the effect is also large: The pass-through is 27 percent larger in an economy with an increase in concentration observed during our sample period from 2005–2019. We verify that the larger pass-through of cost shocks in more concentrated industries is not driven by a positive differential response in endogenous costs, such that the implied price elasticities with respect to costs increases in concentration. Along with the stronger pass-through to prices, we also find that output drops significantly more in concentrated industries, lending additional credibility to the supply interpretation.

We further extend our model to allow for an asymmetric pass-through of cost shocks depending on the sign of the shock. On average, across industries, we do not find significant asymmetric pass-through. However, our results show that more concentration increases the pass-through of positive cost shocks (increases in cost) into prices, while the pass-through of negative cost shocks does not differ significantly depending on industry concentration. (Again, identification rests on within-industry changes of concentration.) In other words, negative cost shocks do not differentially shift the supply curve in concentrated industries, while positive cost shocks do. Consistent with the supply interpretation, we again show that output contracts more after a positive cost shock as concentration increases along with the differential increase in price (no differential output response after a negative cost shock).

Together these results suggest that the rise in concentration is an important factor in the ongoing surge in inflation in the post-COVID period. While current inflationary pressures likely originate in supply shocks, our findings show that concentration is an amplifying factor in the pass-through of theses shocks (but not the cause). Specifically, we find a stronger pass-through in a concentrated economy, driven almost exclusively by *positive* cost shocks, which is exactly what most sectors experienced during and after the COVID-19 pandemic. Therefore, our findings can also reconcile that high industry concentration is an important factor driving higher inflationary pressures post COVID but not necessarily during the past two decades in which no large positive cost shocks occurred and inflation remained muted despite significant increases in concentration.

To better understand the economic mechanism, we use firm-level data to estimate how operating margins respond to cost shocks. We show that cost shocks significantly reduce margins, on average, across all firms and industries, in line with a pass-through smaller than one. But a within-industry analysis reveals that, consistent with market power, the decline in margins of industry leaders (the top 5% of firms according to sales) is significantly muted in more concentrated industries. In fact, industry leaders are able to shield their profit margin entirely from cost shocks. In light of the strong asymmetric pass-through to prices and output at the industry level, we also estimate asymmetric margin responses at the firm level. In line with the price and output responses, the results indicate that positive cost shocks drive the average responses of margins. Finally, we find some evidence that leaders' margins increase in response to shocks to competitors' costs. The firm-level analysis of margins allows us to speak to the literature that relates pass-through to firm size and market shares. Although we do not observe firm-level prices, we do find a nonlinear relationship between size and margins, as larger firms keep higher margins than small firms, after a given cost shock. This is consistent with the nonlinear relationship of pass-through and size documented at the firm level in Feenstra et al. (1996) and Garetto (2016).

While we stress that our analysis does not require that industry concentration is associated with market power, we believe such an interpretation is consistent with the evidence presented in this paper. First, our sample is comprised of the period for which the literature finds concentration is associated with an increase in market power (e.g., Covarrubias et al., 2020). Second, our identifying variation in concentration is within-industry and relative to trend and various fixed effects, and recent findings in the IO literature suggest that within-industry changes in the HHI can be used as a proxy for changes in market power in various cases, such as following M&A episodes (e.g., Nocke and Schutz, 2018; Nocke and Whinston, 2020; Miller and Sheu, 2021). Third, our finding that cost shocks in more highly concentrated industries lead to a larger increase in prices as well as a larger decline in output implies a lower demand elasticity. This empirical core result does not require any structure on the underlying demand system. While we acknowledge that market power is characterized by a firm-level residual demand that is not completely elastic, our industry-level results can be consistent with lower firm-level demand elasticities.[8] Finally, a market power interpretation is also supported by our firm-level findings that, within industry, leaders are able to maintain a high profit margin relative to followers in concentrated industries by passing through cost shocks to prices.

Related Literature. Our paper contributes to various strands of the literature. First, we contribute to the recent empirical and theoretical literature that studies the effect of concentration and market power on macro variables in general. The literature has found that various secular trends can be partially attributed to the increase of concentration and market power, such as the decrease in labor share (e.g., De Loecker et al., 2020; Barkai,

[8]That said, identification of the underlying forces that affect the firm-level residual demand (super) elasticities, such as product differentiation, strategic interactions, or others, is beyond the scope of this paper. Thus, our paper does not aim to explain the reasons behind the observed increase in industry concentration in the Untied States.

2020), increase in savings supply (Farhi and Gourio, 2018), under-investement (Gutiérrez and Philippon, 2017), and overall aggregate productivity growth (e.g., Liu et al., 2022; Farhi and Gourio, 2018). A closely related literature documents the rise of superstar firms and its implications for aggregate dynamics (e.g., Olmstead-Rumsey, 2019; Autor et al., 2020). Our paper contributes to this literature by providing evidence of a different channel—increases in the cost-price pass-through—through which concentration and market power significantly affects macroeconomic outcomes.

Second, this project also contributes to the large literature on estimation of cost pass-through. The empirical literature has so far focused mostly on specific cost shocks (e.g, such as exchange rates, taxes, fuel and energy prices, minimum wage) and/or specific industries.[9] We contribute to this literature by estimating the cost pass-through for industry-wide shocks on all operating expenses in a broad set of industries. Our almost full pass-through result one period ahead is in contrast with most of the exchange-rate pass-through literature (e.g., Koujianou Goldberg and Hellerstein, 2013) that typically find substantially incomplete pass-through. Nakamura and Zerom (2010) estimates that almost all of the gap is due to non-traded costs and strategic considerations—both of which are captured in our analysis.

Third, our paper also belongs to the literature that studies the relationship between market structure and cost pass-through. From a theoretical perspective, the effect of market power on cost pass-through is ambiguous both at the firm and industry level. At the firm level, the standard intuition (e.g., from a textbook Cournot model) is that more market power makes prices *less* cost-reflective and hence reduces the rate of cost pass-through. However, this result can be easily overturned in more realistic settings.[10] Consistent with this theoretical ambiguity, the empirical industrial organization literature has also found different signs and for the relationship between pass-through and market power when studying specific industries.[11] At the industry and aggregate levels, the cost pass-through combines an aggregation of firm-level pass-through, heterogeneous exposure to the shock, strategic complementarities, general equilibrium effects and other factors (see, for instance, the aggregation results in Amiti et al., 2019; Baqaee and Farhi, 2020). Therefore, the relationship between market structure and industry and aggregate pass-through is also ambiguous. Our

[9]For instance, see Goldberg and Knetter (1997), Burstein and Gopinath (2014) for reviews of the early literature on exchange rate pass through. For other settings, see Nakamura and Zerom (2010), Fabra and Reguant (2014), Harasztosi and Lindner (2019), Miller et al. (2017), Ganapati et al. (2020) among many others.

[10]For instance, Ritz (2019) shows that the usual intuition can be overturned simply by reasonably relaxing the assumption of constant marginal costs or log-concavity of demand. For a summary of cost pass-through in various demand systems with variable demand elasticity and markups, see Arkolakis and Morlacco (2017).

[11]For instance, Genakos and Pagliero (2019) and Duso and Szücs (2017) find that market-power decreases pass-through, whileMiller et al. (2017), Ganapati et al. (2020) and Harasztosi and Lindner (2019) find the opposite.

empirical results discipline this theoretical ambiguity. Our estimation leverages industry-level cost-shocks, and thus speak directly to a combination of the underlying demand system, marginal cost curvature and various other features in theoretical models of aggregate pass-through of cost-shocks.

Fourth, our results also speak to the literature on asymmetric pass-through of costs. There is a long standing literature, following the seminal paper by Peltzman (2000), that studies asymmetric pass-through to costs. The main result of this literature is that prices rise faster than they fall in two thirds of industries. Theoretically, there are various reasons why pass-through may be asymmetric (e.g., vertical integration, consumer search costs, kinked demands, adjustment costs, or simply curvatures of supply and demand) and why this asymmetry can change with market-power. Moreover, Ritz (2015) argues that, from any given starting point, a pricing function that is convex in costs will result in asymmetric pass through, and shows that such convexities may arise both in both perfect and imperfect competition. Hence, one cannot identify whether a market is competitive or not from the asymmetry of the cost response alone. Although we can't point to the exact theoretical mechanism behind our empirical findings, our results indicate that from an aggregate perspective the pass-through of the cost shocks we identify are symmetric on average, and that more concentration increases the pass-through of positive cost shocks (increases in cost) to prices, while pass-through of negative cost shocks does not differ significantly depending on industry concentration.

Finally, we also contribute to the literature focused on the importance of idiosyncratic shocks for aggregate fluctuations. (e.g., Gabaix, 2011; Carvalho and Gabaix, 2013; Di Giovanni et al., 2014; Carvalho and Grassi, 2019; Gaubert and Itskhoki, 2021; Chodorow-Reich et al., 2021). Through our instrumental variable approach based on Gabaix and Koijen (2020), we leverage the granularity of the data to construct a measure of industry cost-shocks that are independent from broad economic conditions and sector specific demand.[12] This papers thus overcomes the major challenge in the identification of the effect of cost shocks on aggregate price dynamics, and how this transmission changes with industry concentration. More broadly, our results highlight that granular (firm-specific) cost shocks can affect aggregate price dynamics.

The remainder of the paper is structured as follows. Section 1 describes the data used in the analysis. Section 2 discusses the cost shock identification and presents average price and output responses. In Section 3, we focus on the heterogeneous pass-through depending on industry concentration, and in Section 4, we explore asymmetric responses depending on

[12]For applications of the GIV, see, for instance, Galaasen et al. (2020), Adrian et al. (2020), and Gabaix and Koijen (2021).

the sign of the shock. Section 6 concludes.

1 Data

Our main analysis uses data at the industry-quarter level and builds on two main data sources. First, we collect balance sheet and income statement data from Compustat, which covers the universe of all public firms in the US. Total Operating Expenses (XOPRQ) is our main cost measure. Operating Expenses is the sum of Cost of Goods Sold (COGSQ)–which include all costs directly allocated to production and Selling, General, and Administrative Expenses (XSGAQ)–which include other costs of operating a business that are not directly tied to the production, such as, non-production employee salaries, sales and marketing. We also use the Compustat data to measure industry sales concentration by the Herfindahl–Hirschman index (HHI) at the 3-digit NAICS industry level.[13] To guarantee our data is representative of the underlying market structure in a given industry, we exclude from our regression analysis industries that have less than 2 firms in Compustat at any moment in our sample and retail industries (NAICS 44/45).[14] We acknowledge that Compustat may not be representative of the entire population of US firms. However, it contains the largest firms, which are publicly traded and are more likely to be price setters. In 2017, total sales in our sample corresponded to roughly 53 percent of the US GDP. More importantly, our analysis depends crucially on the availability of quarterly data on firms' costs, information not available, or not at the frequency, in other datasets.[15]

As the second data source, we use producer price data from the Bureau of Labor Statistics (BLS) at the 3-digit NAICS level. We exploit the availability of producer prices at the industry level to link within-industry across time variation in concentration to estimate the effect of cost shock on prices. Moreover, the effect of concentration and market power is likely more relevant for wholesale prices (Gopinath and Itskhoki, 2011) than consumer prices. A firm-level analysis of the cost-price relationship is not feasible given the lack of broadly available firm-level price data for firms in the U.S. To measure the effect of concentration on real outcomes, we also collect data on industry employment and output from the BLS

[13]The HHI is computed, for each industry, as the sum of the squared sales share of each firm.

[14]We exclude retail industries because they have a small number of firms in Compustat. In addition, regional concentration is more important than total industry-level concentration (see, for instance, Rossi-Hansberg et al. (2018)) for retail. Our results are robust to changing these filters to simply exclude industries with less than 20 firms at any moment in our sample. As standard in the literature, we also exclude the Postal Service (NAICS 491), Utilities (NAICS 22), Finance and Insurance (NAICS 52), and Public Administration (NAICS 91/92).

[15]For instance, the Census Bureau Longitudinal Business Database collects information for all US business with paid employees covering all industries at an annual frequency.

at the same 3-digit NAICS level. Our sample for the regression analysis is comprised of 35 industries. The sample period used in our main analysis runs from 2005Q2 through 2019Q4 and is overall constrained by the availability of PPI data, in particular before 2004.[16] We exclude the COVID crisis from our baseline analysis, but our results are robust to extending our sample through 2022Q1.

Appendix Figure B.2 shows the year-over-year inflation rate in our dataset (industry-sales weighted or unweighted) and for comparison, inflation measured by the Consumer Price Index (CPI) and PPI (All Commodities). While the overall pattern is very similar across inflation measures, producer price inflation is much more volatile than consumer price inflation, with an about 8 times standard deviation in the year-over-year change in prices. The magnitude of our estimated effects must thus be interpreted accordingly, as they refer to the more volatile producer prices.

As with prior studies in this area, our analysis is subject to several empirical measures for market power and concentration. First, the definition of a market is subject to debate. Following the common practice in the literature, we use a definition based on industry classifications. Specifically, we compute market shares among Compustat firms in a given NAICS industries. Second, as with other studies that leverage Compustat to measure market concentration, sales values reported in Compustat refer to the sales values of the publicly listed entities in the US. However, sales are not broken down by geographic region but instead refer to the company's consolidated sales, including sales in foreign countries, thereby not singling out sales within the US. However, De Loecker and Eeckhout (2018) use Worldscope to compute firm revenue shares using global information and their results for US firms are consistent with earlier findings using Compustat US only.

Moreover, the set of goods and services included in the PPI provided by the BLS comprises the entire marketed output of US producers, that is establishments in the US by both public and private firms, while our sample of firms includes only firms from Compustat. This is not problematic for our approach for two reasons. First, by leveraging the granularity of the data, most of the industry shocks would come from the largest firms within each industry. (In Gabaix and Koijen (2020) it is even suggested to take this approach even if data from all firms' were observed). Second, although the level of industry concentration measured by the HHI computed from Compustat can be different than that obtained from Census data (Ali et al., 2008), our identification rests of within-industry *changes* in HHI in a time window where increases in concentration have been been associated with an increase in market power

[16] Our sample starts at 2004Q2, and our actual analysis at 2005Q2 due to our econometric specification that includes four lags of dependent and independent variables. When computing firms' innovations, we use data until 2018Q4, and producer prices and output until 2019Q4 when projecting four quarters ahead.

(Covarrubias et al., 2020). Our results are robust to alternative measures of concentration, such as the share of sales by the top 5 firms in a given industry. Finally, from a broader perspective, all of these measurement challenges in the market definition and sample of firms would tend to attenuate our estimates, and thus our results can be seen as a lower bound of the effect of concentration and market power on cost pass-through.

Table 1 reports the industries in our final regression sample and relevant statistics on market shares, concentration, and margins. Since the premise of the paper is based on the increase in market concentration during our sample, we show, by industry, the HHI, average margin, and average margin of the largest 5 firms in each industry at the beginning and our sample, that is, in 2005Q2, and the change between the beginning and end (2019Q4). The table also shows the sector size measured by sales (as percent of total sales). The vast majority of industries—defined at the 3-digit NAICS—observed an increase in concentration measured by the Herfindhal index. In addition to broad increase in industry concentration, we also see that, on average, margins have increased during our sample too, not only in the largest 5 firms in any given industry, but also in the rest of firms.

Table 1: Summary Statistics for Baseline Estimation Sample

	Num firms		HHI		Margin		Margin, top 5	
	Start	Delta	Start	Delta	Start	Delta	Start	Delta
Oil & Gas Extraction	4.26	-2.49	0.19	-0.14	0.28	0.14	0.18	0.25
Mining (ex. Oil & Gas)	0.79	0.41	0.09	0.01	0.32	0.04	0.44	-0.01
Support Activities for Mining	0.85	0.13	0.12	0.02	0.25	-0.08	0.21	-0.05
Food Manuf.	3.16	0.30	0.06	-0.00	0.08	0.01	0.09	-0.10
Beverage & Tobacco Product Manuf.	3.13	-0.44	0.11	0.02	0.21	-0.10	0.27	-0.18
Textile Mills	0.05	-0.03	0.16	0.19	-0.15	0.31	-0.19	0.35
Textile Product Mills	0.09	0.00	0.70	0.04	0.12	0.02	0.12	0.02
Apparel Manuf.	0.59	0.69	0.05	0.17	0.11	-0.13	0.12	-0.21
Leather & Allied Product Manuf.	0.33	0.19	0.29	0.12	0.14	0.01	0.15	-0.00
Wood Product Manuf.	0.57	-0.29	0.26	-0.15	0.15	-0.04	0.15	-0.05
Paper Manuf.	1.88	-0.52	0.08	0.01	0.16	0.04	0.17	0.03
Printing & Related Support Activities	0.29	-0.12	0.16	0.00	0.14	-0.00	0.14	-0.02
Petroleum & Coal Products Manuf.	22.44	-1.82	0.10	-0.01	0.17	-0.06	0.16	-0.02
Chemical Manuf.	12.04	-0.30	0.02	0.00	0.20	-0.01	0.21	-0.09
Plastics & Rubber Products Manuf.	0.71	-0.33	0.12	0.06	0.11	0.03	0.11	0.03
Nonmetallic Mineral Product Manuf.	0.64	-0.34	0.15	0.04	0.08	0.10	0.05	0.12
Primary Metal Manuf.	2.84	-0.26	0.05	0.04	0.21	-0.21	0.25	-0.32
Fabricated Metal Product Manuf.	1.06	-0.11	0.07	-0.01	0.14	0.01	0.18	-0.03
Machinery Manuf.	4.60	-0.46	0.03	0.00	0.12	0.05	0.15	0.02
Computer & Electronic Product Manuf.	10.70	2.99	0.02	0.03	0.15	0.09	0.16	0.12
Electrical Equipment, Appliance, & Component Manuf.	3.37	-0.69	0.14	-0.00	0.08	0.04	0.07	0.05
Furniture & Related Product Manuf.	0.31	-0.02	0.08	0.00	0.10	0.02	0.10	0.04
Miscellaneous Manuf.	0.97	0.22	0.03	0.03	0.19	0.03	0.24	0.04
Merchant Wholesalers, Durable Goods	2.44	0.16	0.04	0.01	0.04	-0.04	0.03	-0.12
Air Transport.	2.62	0.75	0.07	0.01	0.08	0.05	0.10	0.05
Rail Transport.	0.68	0.05	0.18	0.03	0.29	0.20	0.30	0.19
Water Transport.	0.44	0.11	0.11	0.00	0.28	0.03	0.24	-0.02
Truck Transport.	0.51	0.02	0.08	0.02	0.08	0.04	0.08	0.01
Support Activities for Transport.	0.16	-0.02	0.16	0.10	0.09	0.09	0.06	0.12
Couriers & Messengers	1.22	0.02	0.27	0.19	0.15	-0.04	0.16	-0.04
Publishing Inds. (except Internet)	1.71	0.94	0.08	0.13	0.22	0.11	0.33	0.06
Farm-product Raw Materials	2.15	1.32	0.07	0.06	0.28	-0.01	0.24	0.02
Petroleum & Petroleum Products	11.14	-0.52	0.04	0.02	0.30	-0.05	0.25	-0.03
Hospitals	0.64	0.25	0.23	0.05	0.15	0.03	0.14	0.03
Accommodation	0.63	0.22	0.09	0.01	0.23	-0.02	0.20	-0.00

Note: Summary statistics for the core estimation sample (for data cuts, e.g., excluded industries, see the data section). Start values represent (mean) values at the beginning of the sample, Delta measures the change between end of sample and beginning of sample. Sales Share is the percent of an industry's sales in total sales. HHI is the Herfindahl index of sales concentration, Margin is defined as sales minus operating expenses relative to sales. Margin, top 5 focuses on the margins of industry leaders. Source: Compustat and authors' calculations.

2 Cost-Shock Pass-Through to Prices

In this section, we exploit firm-level data to identify cost shocks at the industry level and estimate their impact on industry prices and output.

2.1 Cost Shock Identification

Because cost and prices are endogenous—higher product demand can lead to an increase in output and costs as well as upward pressure on prices—we use firm-level cost data to construct an exogenous industry-level cost shock entirely driven by idiosyncratic firm factors. To do so, we leverage the Granular Instrumental Variable method recently developed by Gabaix and Koijen (2020). The GIV approach combines two key insights. First, one can use firm-level data to identify firm-level idiosyncratic cost changes, that is, changes in cost that are exogenous to the overall evolution of the economy (or industry) and specific to a given firm. Second, due to the granularity of the firm-size distribution, that is, the fact that a few large firms account for a large share of the economic activity in a given industry, we have that these arguably exogenous idiosyncratic cost changes from the first insight contain exogenous variation of the aggregate cost changes at the industry level.

Our GIV approach to isolate industry-level cost shocks is based on two steps. First, we recover firm-level idiosyncratic cost shocks as the residuals from a regression of firm-level log cost on various fixed effects and controls. The idea is to control for industry-trends and firm-trends in costs to isolate idiosyncratic changes in firm costs. Specifically, identification of these idiosyncratic cost innovations is based on the following regression model:

$$\log Cost_{j,t} = \alpha_j + \beta_j \cdot t + \alpha_{i(j),t} + \sum_{k=1}^{4} \rho_k \log Cost_{j,t-k} + X'_{j,t}\gamma + \varepsilon_{j,t}, \tag{1}$$

where $Cost_{j,t}$ is, in our baseline analysis, Operating Expenses of firm j at quarter t $\alpha_{i(j),t}$ is an industry-time fixed effect, α_j is a firm fixed effect, $\beta_j \cdot t$ is a firm-specific deterministic linear time trend, and the vector $X_{j,t}$ contains other firm-level controls depending on the exact model, including sales, assets, and leverage in our most comprehensive specification. As discussed, the purpose of these controls and fixed effects is to take into account any demand-driven trends in firm costs. With this set of fixed effects, cost innovations thus present deviations from industry-time averages and firm-trend deviations. They can be interpreted as percentage innovations to the firm-level costs that are not explained by aggregate demand factors, which are captured by the different fixed effects and firm level controls.

Table 2 reports the regression output for the five different specifications used in this paper. Column (1) presents the least stringent specification, which only includes industry*time fixed effects. Column (2) instead includes firm fixed effects and time fixed effects. Column (3) presents our baseline model that includes industry*time fixed effects, firm fixed effects, and a firm-specific time trend. Unless otherwise noted, all results in the paper refer to this GIV estimation. Columns (4) and (5) include sales, assets, and leverage, with time-varying

Table 2: Models used to Residualize Firm-Level Cost

	(1)	(2)	(3)	(4)	(5)	(6)
Observations	251,383	251,016	251,016	232,534	190,849	184,791
Industry*Time FE	Yes	No	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	No	No	No
Firm FE	No	Yes	Yes	Yes	Yes	Yes
Firm*Time-Trend	No	No	Yes	Yes	Yes	Yes
Time*Log_Sales	No	No	No	Yes	Yes	Yes
Time*Log_Assets	No	No	No	No	Yes	Yes
Time*Leverage	No	No	No	No	Yes	Yes
Time*Lag_Log_Sales	No	No	No	No	No	Yes
Time *Lead_Log_Sales	No	No	No	No	No	Yes
R2	0.984	0.985	0.987	0.992	0.993	0.994
RMSE	0.344	0.333	0.314	0.225	0.210	0.195

Note: All models include four lags of the dependent variable. Model (3) represents our baseline model to compute the firm-level cost innovations underlying the GIV construction.

coefficients. From the table output, it is clear that our set of controls and fixed effects accounts for a large share of the variation in cost both across and within industry, and also within firm.

In the second step, to construct our GIV cost shock at the industry level, we compute the weighted average of the firm-level, j, residuals by industry, i:

$$GIV_{i,t} = \sum_{j \in i(j)} w_{j,t-1} \hat{\varepsilon}_{j,t}. \tag{2}$$

where the weights $w_{j,t-1} = \frac{\text{Sales}_{j,t-1}}{\sum_k \text{Sales}_{k,t-1}}$ represent the within-industry sales share of firm j at time $t-1$. Thus, the cost shock of larger firms have larger weights. In robustness version, we also consider aggregation schemes where we compute the weighted sum for the residuals of only the largest 5 firms within a given industry. As we show below, our results are robust to these variations.

Appendix Table C.1 shows summary statistics of the identified cost shocks. First, note that all shocks have a small, but positive, mean, driven by some right skew of the distributions. The interquartile range is in general close to zero with weighted mean percentage costs innovations varying from around -2 percent to around 3 percent. Second, as the model of firm-level costs becomes more saturated the variance of the industry-level cost shocks declines. Third, the distribution has fat tails with some large cost shocks, both positive and negative. Given the aggregation scheme from firm-level percentage innovations to cost to the industry level, the cost shocks can be interpreted as the sales-share-weighted mean of percentage cost innovation within industry.

In Appendix Table C.2, we present the pairwise correlations between our different cost measures. All shock measures are positively correlated and the correlation is not surprisingly stronger for more similar specifications. Especially, models that include industry-time fixed effects, firm fixed effects, and firm-specific time trend, exhibit a high correlation of about 0.8. These models also explain the largest share of variation in the firm-level cost. Despite small differences, as we will discuss, the different cost shocks yield similar impulse response estimates. Therefore, we focus in our discussion on the baseline model (3).

We can directly verify the supply-shock interpretation of the identified firm-level cost innovations underlying the industry-level GIV cost shock by comparing them with the narrative information reported in the quarterly reports filed with the SEC (10-Q). Because the large panel renders a comprehensive discussion of each firm's shocks unfeasible, we discuss a few examples of large cost innovations for firms in different industries in Appendix A. Overall, our review of the firm-level cost innovations lends additional credibility to the GIV shocks (and their interpretation as supply shocks) that are at the core of our analysis.

Our main analysis relies on the GIV to compute aggregate supply shocks. This approach is appealing because it allows us to directly compute aggregate cost shocks from individual firms' accounting data, exploiting the granularity of the firm-size distribution. However, the GIV measure relies on the firm-size distribution being heavy tailed, which is necessarily related to industry concentration. As a robustness check, we redo our analysis with a different supply shock variable computed based on the Global Supply Chain Pressure Index (GSCPI) made available by the NY Fed.[17] We use this aggregate index in combination with the input-output (I/O) matrix for the United States to compute industry-specific supply shocks that take into account both an industry's direct and indirect exposures to disruption in the international supply of production factors. Specifically, let $A \equiv [a_{i,j}]$ be an $N \times N$ matrix with elements $a_{i,j}$ collecting the value of inputs into the production process of industry i sourced *domestically* (i.e., from within the US) from industry j relative to the total value of all inputs and labor costs (adjusting for taxes and subsidies) of industry i. Further, let m be an $N \times 1$ vector with elements m_i representing the value of all inputs sourced by industry i from abroad (outside of the US) relative to the total value of all inputs and labor costs

[17]The GSCPI is based on a number of commonly used metrics to provide a summary of supply chain disruptions. Global transportation costs are measured by employing data from the Baltic Dry Index (BDI) and the Harpex index, as well as airfreight cost indices from the U.S. Bureau of Labor Statistics. The GSCPI also uses several supply chain-related components from Purchasing Managers' Index (PMI) surveys, focusing on manufacturing firms across seven interconnected economies: China, the euro area, Japan, South Korea, Taiwan, the United Kingdom, and the United States. For more details see https://www.newyorkfed.org/research/policy/gscpi#/overview.

(adjusting for taxes and subsidies) of industry i. We then compute the vector $(I-A)^{-1}m$, which is a measure of industries' dependencies on the foreign supply of production factors through both direct and indirect exposures. Multiplying this vector of industry exposures with the GSCPI gives our alternative supply shock measure.

2.2 Cost-Shock Pass-Through

We use local projections to estimate the dynamic pass-through of the identified cost shocks to prices and other key outcome variables. Specifically, the response of prices h period after impulse are estimated using the following empirical specification at the industry i, quarter t level:

$$\log PPI_{i,t+h} = \beta^h GIV_{i,t} + X'_{i,t}\gamma^h + \alpha_i^h + \alpha_t^h + \varepsilon_{i,t+h}, \tag{3}$$

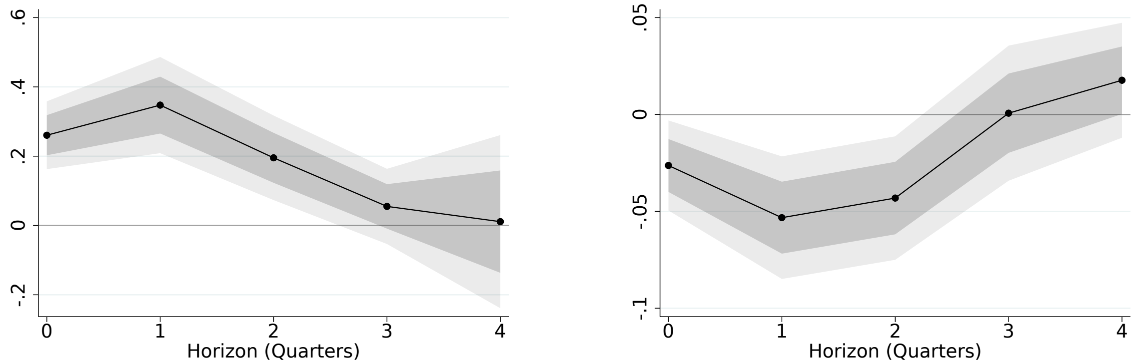
where $\log PPI_{i,t}$ is the logarithm of the producer prices index, $GIV_{i,t}$ is the industry-level cost shock. Our main goal is to identify the response of prices. However, we also estimate the responses of other key variables to cost shocks, like output, endogenous costs, or the GIV itself. Time t is measured in quarters. The vector of controls includes four lags of the dependent variable, four lags of the GIV shock, and a industry-specific linear time trend.[18] The model also includes industry and time fixed effects. As a result of this model specification, β^h presents the the effect of a cost increase on price h periods ahead, measured as a percent deviation (log difference) from the local level of the response variable, i.e., the industry-specific deviation from the cyclical and trend component of prices. Moreover, to improve estimation efficiency, we include lags of the shocks to take into account potential residual autocorrelation in the shocks. We base our inference on standard errors clustered at the industry-level and thereby allow for general correlation structure of residuals within a given industry as they arise from the local projections. Finally, because we are interested in the aggregate cost-price pass-through, we run weighted regressions using an industry's share in aggregate sales as weights.

Figure 2, Panel (a), shows the estimated average response of prices to a cost shock. The cost shock leads to a significant increase in prices relative to the local trend growth. The price effect materializes upon impulse, with an estimated response of 0.26, and lasts for 2 quarters after the shock, with the peak response in the quarter after the shock (coefficient of 0.35). These results are robust to using GIV shocks estimated under alternative assumptions and also robust to estimating the equations in growth rates instead of levels.[19] Panel (b)

[18] Results are robust to modeling deterministic industry-specific time trends with higher order order polynomials.

[19] Appendix Figure B.3 shows similar results when we use alternative GIV shocks based on different set of controls and when we aggregate the residualized cost innovations of industry leaders only. Appendix Figure

Figure 2: Price and Output Responses to Cost Shock



(a) Prices on GIV

(b) Output on GIV

Note: The figure shows estimates from local projections of log PPI (Panel (a)) and log output (Panel (b)) on the cost shock (GIV), that is, the $\beta^h, h = 1, ..., 4$ in equation 3. The specifications include a set of controls and fixed effects, such that responses are interpreted as deviations from local trend growth. Light shading indicates 90 percent confidence intervals, and dark shading indicates one standard error bands.

reports the response of real industry-level output, which we estimate using an analogous version of (3). Economic activity significantly contracts after a cost shock along with the increase in prices. Similar to the price response, the effect on output lasts up to 2 quarters after impact with a peak response at horizon $h = 1$. These findings on prices and quantities together lend additional credibility for the interpretation of a supply shock.

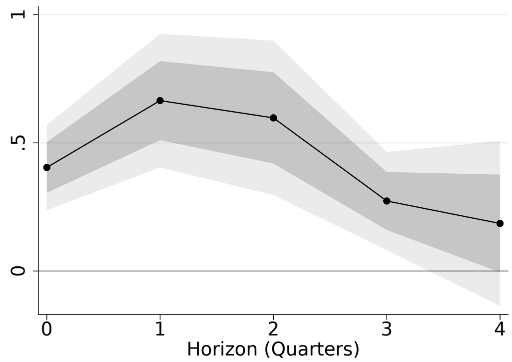
In Figure 3, we show the response of endogenous costs to an identified exogenous cost shock. Panel (a) shows that, in response to the cost shock, operating expenses increase relative to trend growth for about three quarters, with a peak response one quarter after the shock, similar to the responses observed for prices and output.[20] The endogenous cost response to the shock contributes to the total supply effects we are seeing in prices and output. On the other hand, Panel (b) shows that the cost shocks are basically serially uncorrelated conditional on controls.

Our core results in Figure 2 present the responses of a reduced form model. We can also uncover the structural form explicitly using local projections with instrumental variables (Stock and Watson, 2018). The structural parameter estimates estimated using this approach yields the price and output elasticities with respect to costs—objects of particular interest in

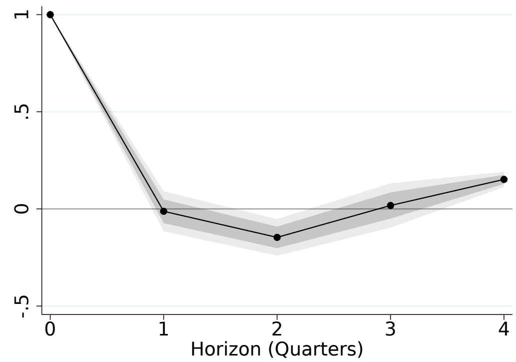
B.4 estimates the responses of price *growth* instead of levels (relative to trend): Consistent with the level response, we find that price growth increases for 2 quarters relative to trend but then is below trend for 2 quarters, such that the levels come back to trend growth.

[20] In the cost responses (Panel (a)) we remove one influential observation (Oil and Gas Extraction in 2011 Q1) to improve smoothness and standard errors of the impulse response function at response horizon $h = 4$. However, we obtain qualitatively similar results for the cost response when using the full sample. We verified that the impulse responses of other variables are not affected by exclusion of this data point.

Figure 3: Cost and Cost-Shock Responses



(a) Cost on GIV



(b) GIV on GIV

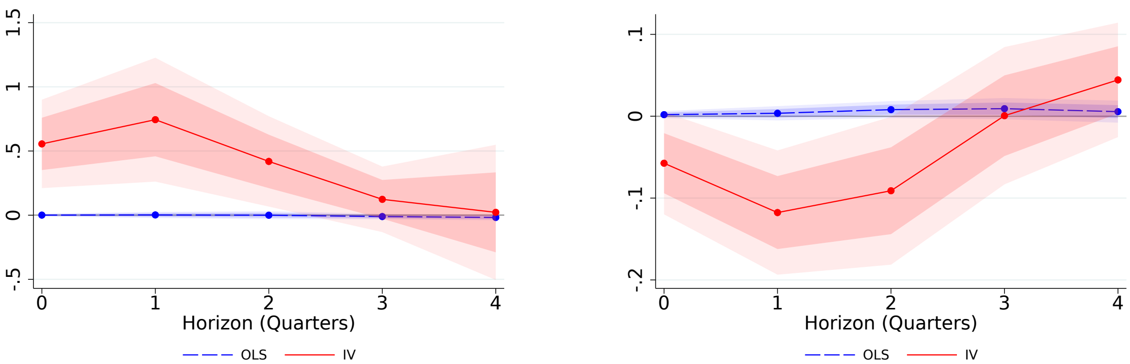
Note: The figure shows estimates from local projections of log Operating Expenses (Panel (a)) and the GIV (Panel (b)) on the cost shock (GIV), that is, the $\beta^h, h = 1, ..., 4$ in equation 3. The specifications include a set of controls and fixed effects, such that responses are interpreted as deviations from local trend growth. Light shading indicates 90 percent confidence intervals, and dark shading indicates one standard error bands.

economic theory and policy questions. Therefore, in equation (3), we swap out the GIV cost shock with the (logarithm of) operating cost. Because cost and prices are endogenous, we exploit the GIV shock as an instrument for the endogenous costs.[21] Panel (a) suggests that a (exogenous) one percent increase in costs is related to about 0.5 percent increase in prices upon impact. Prices increase up to about 0.7 percent one quarter after the cost increase. A complete pass-though coefficient of 1 is included in the 90 percent confidence interval . In contrast, the biased OLS estimates reported in blue are close to zero for all horizons. This is consistent with the idea that costs and prices move due to both supply and demand shocks, such that a naive analysis of costs and price changes is likely to be biased toward zero and capture neither demand or supply factors. This result further highlights the importance of using exogenous variation in costs to estimate this key elasticity. Panel (b) reports the same IV estimates for output. Although standard errors are larger compared to those of the reduced form model, the point estimates are negative throughout horizon 2, indicating an output elasticity of close to –0.1 at horizon $h = 1$.

In many theoretical models, profit maximization links optimal price setting to marginal costs, while fix costs determine firm entry and exit. Therefore, we next provide estimates of price response to different types of cost shocks. Unfortunately, accounting cost measures do not sharply distinguish between the economic concepts of variable and fixed costs, as

[21]First-stage diagnostics support the relevance of the instrument with robust F statistics of substantially larger that the commonly applied threshold of 10 in all model specification and a rejection of an LM test of underidentification.

Figure 4: OLS vs IV Estimates of Implied Elasticities



(a) Prices on Cost

(b) Output on Cost

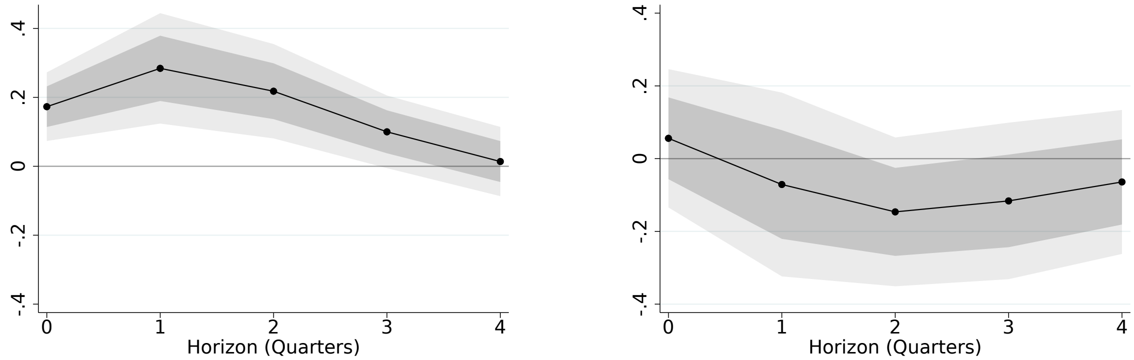
Note: The figure shows estimates from local projections of log PPI (Panel (a)) and log output (Panel (b)) on Operating Expenses. Red impulse responses present IV estimates using the GIV as an instrument for Operating Expenses, while blue responses use OLS. The specifications include a set of controls and fixed effects, such that responses are interpreted as deviations from local trend growth. Light shading indicates 90 percent confidence intervals, and dark shading indicates one standard error bands.

discussed before. Yet, we can test the response to different accounting measures that are more closely linked to one or the other. To do so, we dis-aggregate our total cost measure (Operating Expenses) into Cost of Goods Sold—arguably a large share of which is variable cost—and Selling, General and Administrative Expense, which contains many lines of fixed costs. Across all firms, the mean of Cost of Goods Sold/Operating Expenses is 0.60 while the median is 0.68.

Figure 5 shows the estimated responses using the variable-cost proxy (Panel (a)) and the fixed-cost proxy (Panel (b)). Consistent with theory, we find that shocks to the variable-cost proxy lead to a significant pass through into prices while shocks to the fixed-cost proxy do not trigger any significant adjustment in prices.

[Work-in-progress] Additionally, we show in the Appendix the baseline responses of prices, output, and costs to the alternative supply shock measure based on the GSCPI along with the exposure (direct and indirect) to international supply of production factors. The results are qualitatively similar to what we obtain using the GIV-based supply shock measure and lend additional credibility to our analysis.

Figure 5: Price Response to Different Cost Shocks (CoGS vs Non-CoGS)



(a) Prices on GIV (CoGS only)

(b) Prices on GIV (Non-CoGS only)

Note: The figure shows estimates from local projections of log PPI on the GIV based only Cost of Goods Sold in Panel (a) (a proxy for variable costs), and on the GIV based only on other costs than Cost of Goods Sold in Panel (b) (a proxy for fixed costs). Across all firms, the mean of Cost of Goods Sold/Operating Expenses is 0.60 while the median is 0.68. The specifications include a set of controls and fixed effects, such that responses are interpreted as deviations from local trend growth. Light shading indicates 90 percent confidence intervals, and dark shading indicates one standard error bands.

3 The Role of Concentration

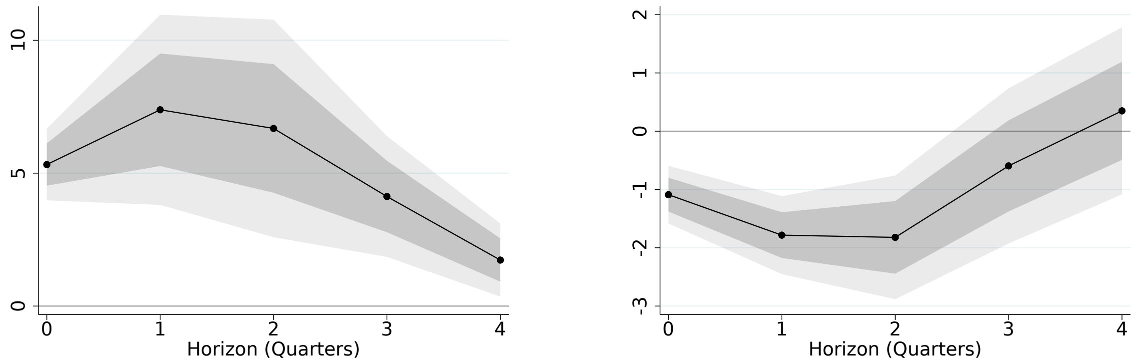
The effect of supply shocks on equilibrium prices and quantities crucially depends on the shape of the demand curve, typically characterized by the (residual) demand elasticity and super-elasticity. A more inelastic (residual) demand allows a firm to charge higher markup over the marginal cost. The degree of markup is often referred to as market power. Given that marginal cost or equivalently demand elasticities are not readily observable, a large literature has argued that market concentration, although not a necessary nor sufficient condition for market power, can nevertheless serve as a good empirical proxy for competition and firms ability to charge markup, at least within industry (Syverson, 2019).

How industry concentration affects the pass-through of cost shocks to prices is the central question of this paper. Therefore, we next estimate heterogeneous pass-through coefficients depending on the industries market concentration. We measure market concentration with the Herfindhal-Hirschman Index (HHI) based on within-industry sales shares:

$$HHI_{i,t} = \sum_j \left(\frac{Sales_{j,t}}{\sum_k Sales_{k,t}} \right)^2 , \tag{4}$$

For simplicity, we assume that the pass-through of cost shocks to prices and output is

Figure 6: Differential Pass-Through Depending on Concentration



(a) Prices on GIV*HHI

(b) Output on GIV*HHI

Note: The figure shows estimates from local projections of log PPI (Panel (a)) and log output (Panel (b)) on the interaction term between cost shock (GIV) and industry concentration (HHI). Light shading indicates 90 percent confidence intervals, and dark shading indicates one standard error bands.

linear in HHI.[22] In terms of our local projections this means that we modify equation 3 by including an interaction term between the GIV and the HHI. Because our focus is on within industry variation in HHI that abstracts from cross-industry differences in HHI that may be correlated with differences in production process, scale ecomomies, etc, we also allow the effect of the cost shock to have heterogeneous effects across industries. Our estimation equation then becomes:

$$\log PPI_{i,t+h} = \beta_i^h GIV_{i,t} + \beta_{HHI}^h GIV_{i,t} \times HHI_{i,t} + X_{i,t}'\gamma^h + \alpha_i^h + \alpha_t^h + \varepsilon_{i,t+h}, \tag{5}$$

where the control vector $X_{i,t}$ now includes in addition to the variables from the model 3 also $HHI_{i,t}$, as well as four lags of $GIV_{i,t} \times HHI_{i,t}$ and $HHI_{i,t}$. Our key coefficient of interest in this model is β_{HHI}^h, which measures the differential pass-through effect depending on HHI.

Given our set of controls, specifically, industry-specific base effects, β_i^h, and lagged HHI, we identify the effect of concentration on the pass-through effectively from changes in HHI within industry. This empirical strategy rules out that we are attributing the pass-through effect of concentration to cross-industry differences in concentration that maybe correlated with other industry-specific variables, such as the degree of scale economies in the production process or its capital intensity.

Figure 6 shows the core result of this paper: Higher concentration significantly amplifies

[22]Such a functional form can be derived in the general setting in Amiti et al. (2019). For that, one needs to assume that firm size is the key dimension of heterogeneity across firms and impose some functional form assumption.

the pass-through of the cost shock to prices and outputs. Panel (a) shows that the pass-through to prices is significantly larger up to four quarters after impact, while Panel (b)) shows that output declines mores strongly for up to three quarters after impact. As Table 3 shows, the differential price response amounts to 5.33 at $t = 0$ and 7.39 at $t = 1$. These statistically highly significant effects are also economically large as a simple back-of-the-envelope calculation shows: Assuming a within-industry change in HHI of 0.03, which is roughly consistent with what we find across all industries, our estimates imply that, at response horizon $h = 0$, the response of prices to cost shocks is about 61 percent larger than the average response of about 0.26 (0.61 = 5.33*0.03/.26). At horizon $h = 1$, our estimates indicate an increase in the response of about 64 percent (=7.39*0.03/0.35) than the average response across all industries.

Given that baseline and subsequent change in HHI is heterogeneous across industries, the results above do not necessarily reflect the increase in pass-through for a representative sector in our sample. Table 3, Panel (a), provides a more precise evaluation of the effect the change in concentration observed since the beginning of this century has on the pass-through of cost shocks. Specifically, our estimates in row (3) take into account industry-specific baseline responses and actual industry-specific changes in HHI (as opposed to a commonly assume change of 0.03) to provide an estimate of the median percentage increase in the response coefficient across industries. Formally, based on our parameter estimates, we compute the median of $\frac{\beta_i^h + HHI_{i,2018}\beta_{HHI}^h}{\beta_i^h + HHI_{i,2005}\beta_{HHI}^h} - 1$. This calculation reveals that, at horizon $h = 0$, the median industry experienced a 27 percent increase in the response to cost shocks due to the increase in concentration. These numbers are somewhat smaller than the ones obtained from a simple back-of-the-envelope calculation done in our baseline evaluation of the quantitative effects, but still economically sizable. Panel (b) shows the same computations for the output response, suggesting that output is 5 percent more responsive to cost shocks at $h = 0$ due to concentration.

Our findings that cost shocks in more highly concentrated industries lead to a larger increase in prices as well as a larger decline in output imply a lower demand elasticity (in absolute values). This empirical result does not require any structure on the demand system. We can obtain demand elasticity estimates by computing $\epsilon \equiv \frac{d \log q}{d \log p} = \frac{d \log q / d \log GIV}{d \log p / d \log GIV}$, and estimate what the changes in price and output responses due to the increase in concentration imply for changes in the demand elasticity. Panel (c) of Table 3 reports the implied percentage change in demand elasticity. The results show that, at $h = 0$, demand has become about 6 percent more **inelastic**.

Importantly, Appendix Figure B.5 shows that the differential price and output responses depending on concentration cannot be explained by a stronger cost increase in concentrated

Table 3: Implied Changes in Pass-Through of Cost-Shocks Due to Increase in Concentration

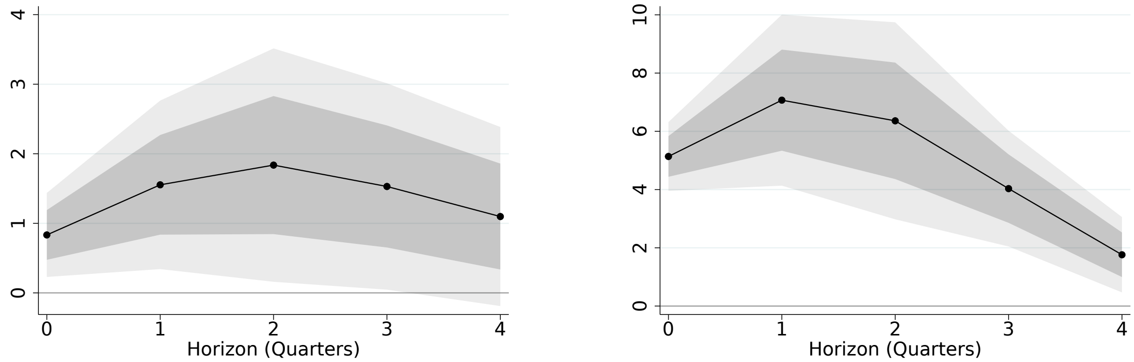
	Horizon (Quarters)				
	0	1	2	3	4
	Panel (a): Prices				
(a) Avg response (β^h_P)	.261	.348	.195	.055	.011
(b) Interaction effect ($\beta^h_{HHI,P}$)	5.325	7.386	6.684	4.121	1.731
(c) Change in Response Due to Increase in Concentration (%)	26.807	16.687	6.281	6.324	6.16
	Panel (b): Output				
(a) Avg response (β^h_Q)	-.026	-.053	-.043	.001	.018
(b) Interaction effect ($\beta^h_{HHI,Q}$)	-1.089	-1.783	-1.821	-.595	1.731
(c) Change in Response Due to Increase in Concentration (%)	5.291	4.593	6.522	2.13	-1.653
	Panel (c): Implied Demand Elasticity				
Change in Demand Elasticity Due to Increase in Concentration (%)	-6.284	-9.401	-2.78	-4.89	-.628

Note: Rows 1a and 2a report the estimates of β^h from equation (3), for either the price (panel 1) model or the output model (panel 2) . Rows 1b and 2b report the estimates of β^h_{HHI} from (5). Rows 1c and 2c report the median of the percentage change in industry-level responses attributed to the increase in concentration during our sample. That is, we compute the median of $\frac{\beta^h_i + HHI_{i,2018}\beta^h_{HHI}}{|\beta^h_i + HHI_{i,2005}\beta^h_{HHI}|} - 1$, where i indexes industries as before, and the parameter estimates are either for prices (panel 1) or output (panel 2) as the response variable. Panel 3 reports the median percentage change in demand elasticity due to in-sample change in HHI as $\left(\frac{\beta^h_{i,Q} + \beta^h_{HHI,Q} * HHI_{i,2018}}{\beta^h_{i,P} + \beta^h_{HHI,P} * HHI_{i,2018}}\right) / \left(\frac{\beta^h_{i,Q} + \beta^h_{HHI,Q} * HHI_{i,2005}}{\beta^h_{i,P} + \beta^h_{HHI,P} * HHI_{i,2005}}\right) - 1$

sectors in response to a cost shock. In fact, we estimate no differential response of costs to a cost shock depending on concentration. In addition to the lack of statistical significance, point estimates are small, especially when compared to those of Figure 6, Panel (a), suggesting that the insignificance differential cost response is also economically small. Moreover, Figure B.5 shows that using endogenous costs, instead of cost shocks, again leads to attenuated estimates of the interaction effect.

Our key finding on the role of concentration is very robust to a variety of different measurement and modelling choices. Figure 7 shows that our core result does not depend on measuring concentration with the HHI. Instead, in Panel (a), we find very similar responses if we use the sales share of industry leaders (largest five firms by sales within an industry) instead of the HHI. Panel (b) shows that we find similar results when we use the excess HHI, defined as $HHI^e_{i,t} = (HHI_{i,t} - 1/N_{i,t})/(1 - 1/N_{i,t})$ with $N_{i,t}$ being the number of firms, to account for entry and exit and hence a varying number of firms within industry over time. In the Appendix, we also find similar results using alternative set of industries (Appendix Figure B.6) and alternative industry shocks (Appendix Figures B.7). We also find consistent results when we estimate the response of price growth as compared to levels (Appendix Figures B.8). Finally, consistent with variable costs playing a more important

Figure 7: Differential Price Response with Alternative Concentration Measures



(a) Price on GIV*Top 5 Share

(b) Price on GIV*HHI (Excess)

Note: Robustness analysis to our main results in Figure 6, Panel (a), using alternative measures of industry concentration: the share of top 5 firms and the excess Herfindhal index (both computed within industry).

role in price setting and our prior result on the level effect, we also find that the differential effect on prices depending on industry concentration is more driven by CoGS as compared to non-CoGS expenses (Appendix Figure B.9).

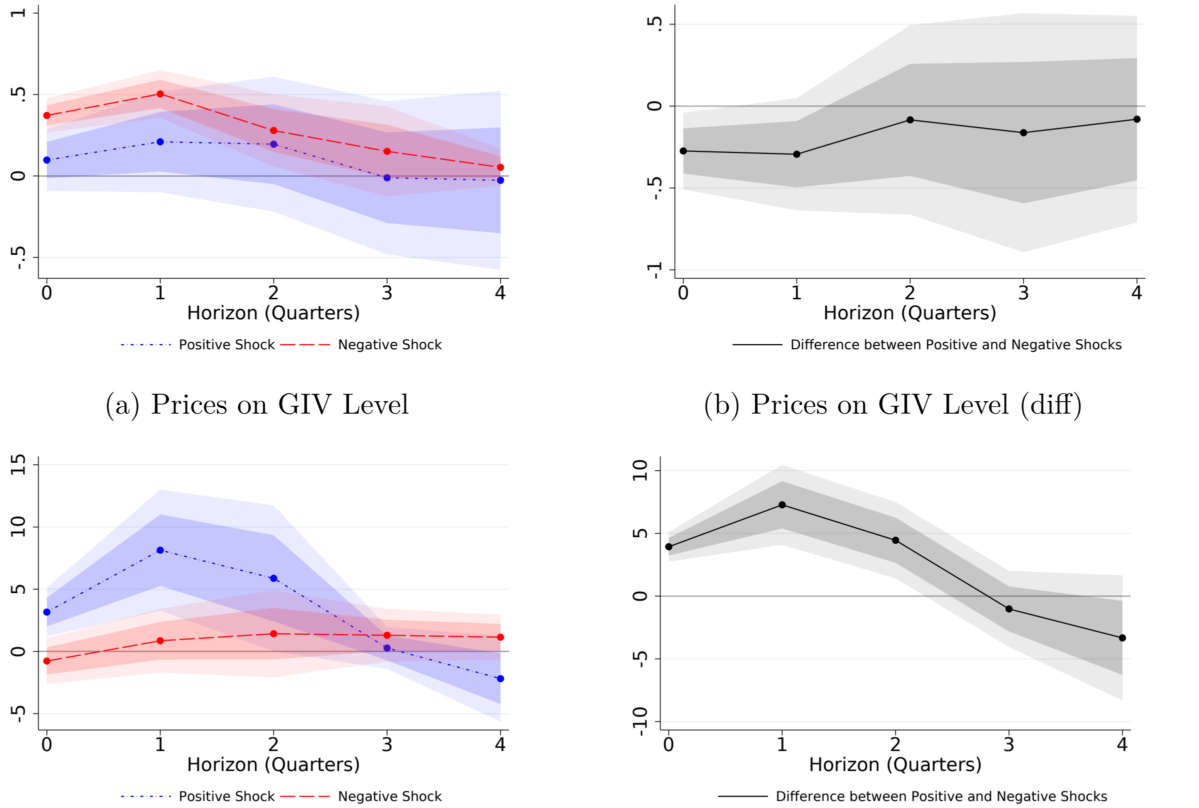
Firm-level demand elasticity, or equivalently markup, is widely used as a measure of a firm's market power. While not based on firm elasticities, our aggregate results are consistent with prior studies that argue that changes in industry concentration are a proxy for changes in market power, at least within industry and in the time frame we analyze. While our results are suggestive of market power, identification of the underlying forces that drive the demand curves, such as product differentiation, strategic interactions or others, is beyond the scope of the paper.

4 Asymmetric Responses to Positive vs. Negative Shock

Several papers argue that prices are subject to downward rigidity, such that cost increases are passed through (more) to prices as compared to cost decreases (e.g., Peltzman, 2000; McShane et al., 2016). Therefore, to understand whether positive cost shocks have a different effect on prices than negative shocks (cost decreases), we next estimate models that allow for an asymmetric pass-through of cost shocks. Our focus is again on the differential effect in pass-through depending on market concentration, so our object of main interest is the coefficient on a triple interaction between our cost shock, the HHI, and an indicator variable that indicates the sign of the cost shock.

Figure 8 presents asymmetric price responses to cost shocks. Panel (a), which presents

Figure 8: Asymmetric Price Responses



(a) Prices on GIV Level

(b) Prices on GIV Level (diff)

(c) Prices on GIV*HHI

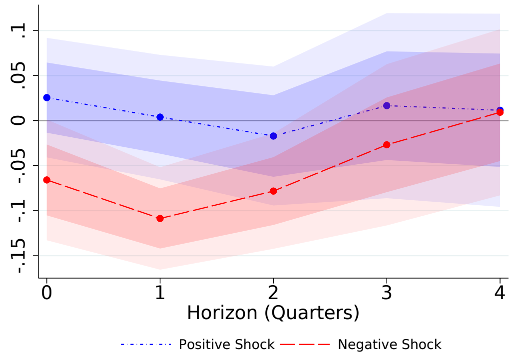
(d) Prices on GIV*HHI (diff)

Note: The figure shows estimates from local projections of log PPI on the cost shock (Panel (a)) and the interaction between cost shock and HHI (Panel (c)). Responses are split depending on the sign of the cost shock: Blue (red) lines represent the responses to a positive (negative) cost shock. The differences between the blue and red lines are shown in Panels (c) and (d). All specifications include a set of controls and fixed effects, such that responses are interpreted as deviations from local trend growth. Light shading indicates 90 percent confidence intervals, and dark shading indicates one standard error bands.

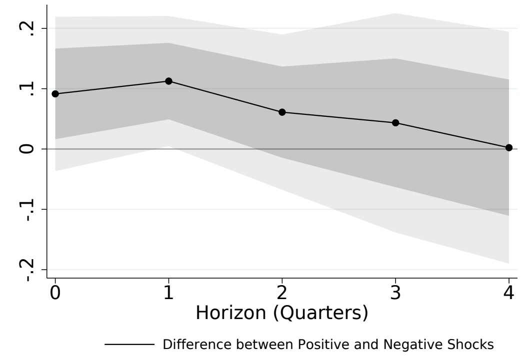
the average effects not differentiating on industry concentration, shows that prices do not respond significantly different to positive versus negative cost shocks (Panel (b) shows the differences along with standard confidence intervals.) On the other hand, Panel (c) reveals an important asymmetric effect depending on concentration: positive cost shocks (increases) are pass-through substantially more compared to negative cost shocks to prices in more concentrated industries. The different pass-through is highly significant at relevant horizons (Panel d). This finding is consistent with downward price rigidity rooted in market power. Appendix Figure B.11 confirms that the asymmetric response depending on concentration is not driven by a differential cost response.

Figure 9 shows asymmetric output responses. Panel (a), which shows the level effect,

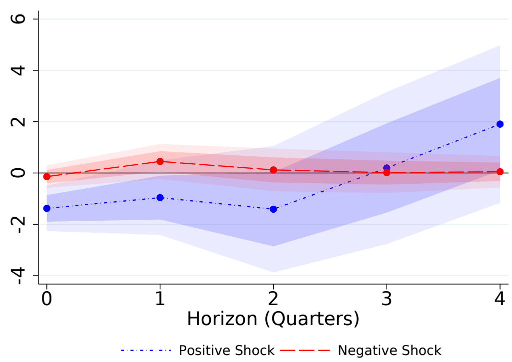
Figure 9: Asymmetric Output Responses



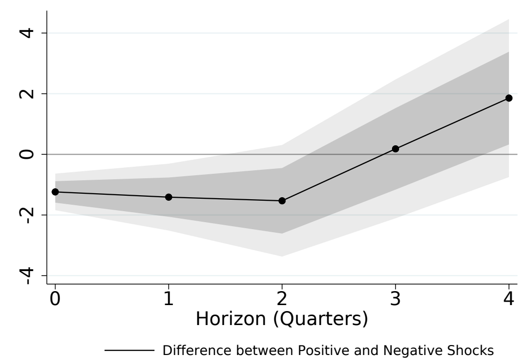
(a) Output on GIV Level



(b) Output on GIV Level (diff)



(c) Output on GIV*HHI



(d) Output on GIV*HHI (diff)

Note: The figure shows estimates from local projections of log output on the cost shock (Panel (a)) and the interaction between cost shock and HHI (Panel (c)). Responses are split depending on the sign of the cost shock: Blue (red) lines represent the responses to a positive (negative) cost shock. The differences between the blue and red lines are shown in Panels (c) and (d). All specifications include a set of controls and fixed effects, such that responses are interpreted as deviations from local trend growth. Light shading indicates 90 percent confidence intervals, and dark shading indicates one standard error bands.

reveals that output increase in response to a negative cost shock, while output does not significantly respond to positive cost shocks. However, the difference is not statistically significant (Panel (b)), similar to the price response. Panel (c) show the asymmetric responses depending on concentration. Consistent with the stronger pass-through of positive cost shocks to prices, we also find that output responds significantly more to negative cost shocks in more concentrated industries.[23]

[23]Note that as a results of the baseline and the interaction term, output does increase in response to a postitive cost shock in concentrated industries.

5 Firm Profit Margins

We next move our analysis on the effect of concentration and market power on the pass-through from the industry level to the firm level. Using firm-level data from Compsutat, we study how firms' profit margins respond in respond to firms' innovation and industry cost-shocks; that is, we consider the join effect of prices and quantity adjustments on firms' profitability. Our main measure of profit margins is the difference between sales and operating expenses, expressed as a share of sales. We estimate analogous local projections to obtain response functions of firm margin to the firm-level cost residuals used in the GIV construction.

Our key focus is to estimate the differential response of margins to cost shocks by leaders in a given industry relative to industry followers. In line with the previous industry-level analysis, we also investigate whether the firms' margin response varies depending on industry concentration, and whether industry leader responses relative to followers vary additionally depending on the concentration of the industry. Formally, we estimate, in our most saturated regression, the following equation by least squares:

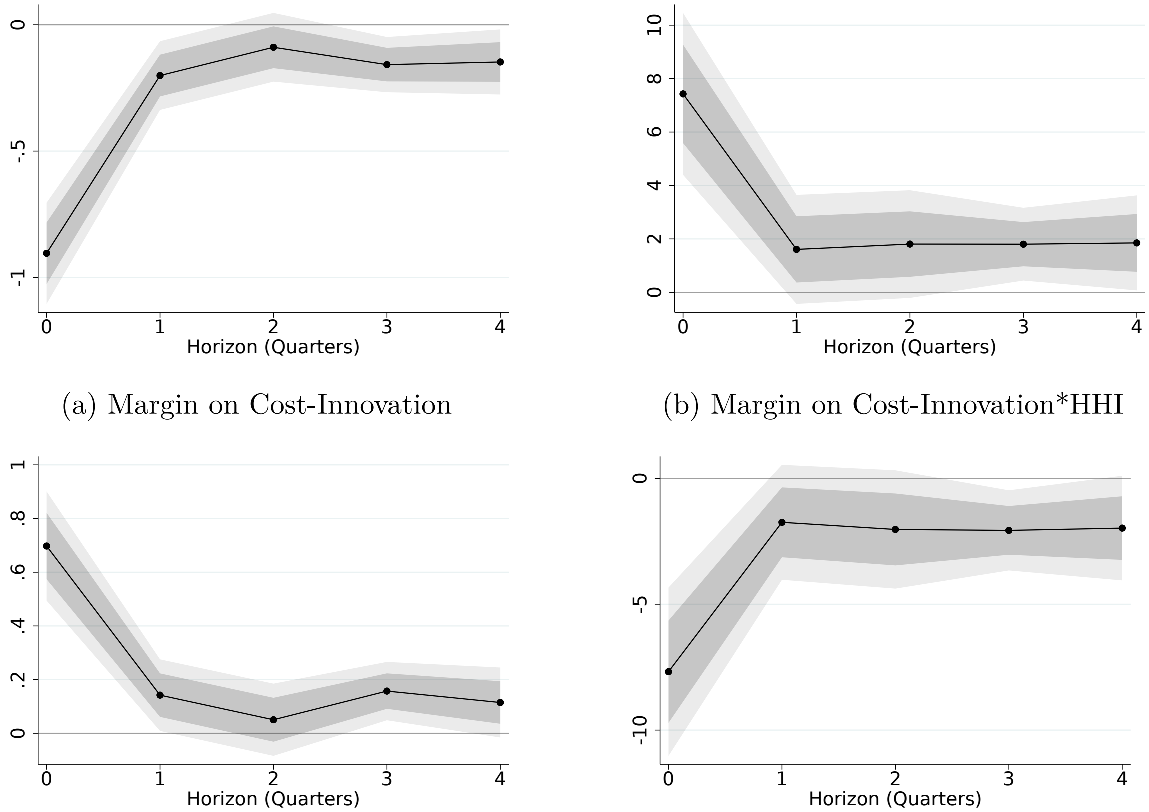
$$\begin{aligned} Margin_{j,t+h} =& \beta_i^h \cdot \hat{\epsilon}_{j,t} + \beta_L^h \cdot \hat{\epsilon}_{j,t} \times Leader_{j,t} + \beta_{HHI}^h \cdot \hat{\epsilon}_{j,t} \times HHI_{i(j),t} \\ &+ \beta_{HHI\times L}^h \cdot \hat{\epsilon}_{j,t} \times HHI_{i(j),t} \times Leader_{j,t} + \alpha_{i(j),t}^h + \alpha_j^h + \beta_j^h \cdot t + \varepsilon_{i,t+h} \end{aligned} \tag{6}$$

where j indexes firms, $i(j)$ is the industry of firm j, and t denotes quarters, as before. Leader is an indicator variable that equals one for the largest 5 firms based on sales within a given industry and quarter. As before, HHI is the Herfindhal index of sales concentration for the industry the firm operates in. Our key focus will be on the differential response of Leaders in a given industry. We also study the effect of industry concentration and whether the leader indicator. Our main results will show first effects without including Cost-Innovation*Leader and Cost-Innovation*HHI, or the triple interaction. We then show results for two models where we include only one of the interaction terms in each. And then the full model with the triple interaction as shown in Equation (6)

The full model specification includes industry*times fixed effects, which allows us to focus on a *within* industry comparison of leader effects. We also include firm fixed effects and a firm-specific (linear) trend to account for additional heterogeneity across firms. Recall that our firm-level cost innovation, $\hat{\epsilon}_{j,t}$, is the innovation used in the construction of the GIV. Economically, these cost innovations represent percentage changes in a firm's operating expenses orthogonal to a large set of fixed effects and controls, see Section 2.1 for details.

Because some firm-quarters in our sample have large negative operating margins with

Figure 10: Margin Response to Cost Innovations at the Firm-Level



(a) Margin on Cost-Innovation

(b) Margin on Cost-Innovation*HHI

(c) Margin on Cost-Innovation*Leader

(d) Margin on Cost-Innovation*HHI*Leader

Note: The figure shows estimates from local projections of profit margin, defined as (sales-operating expenses)/sales on the cost shock (Panel (a)), the interaction between cost shock and HHI (Panel (b)), the interaction between cost shock and industry leader indicator (Panel (c)), and the triple interaction between cost shock, HHI and industry leader indicator (Panel d). All lower-level interaction terms are included in the specification, but only the relevant estimates are plotted. The data are at the firm-quarter level. All specifications include a set of controls and fixed effects, such that responses are interpreted as within-industry deviations from firm-specific local trend growth. Light shading indicates 90 percent confidence intervals, and dark shading indicates one standard error bands.

a large influence on our estimates and specifically standard errors, we exclude observations with negative margins from our regressions.[24] However, as we show in robustness analysis, the inclusion of negative-margin observations, while it has large quantitative effects on our estimates, does not qualitatively change the key insights as discussed below. Finally, we base our inference on robust standard errors clustered at the firm level.

[24] In general, firms with negative margins tend to be smaller. Overall, more than one quarter of firm-quarters in the sample have negative margins, and about 5% of firm-quarters in our full sample have negative margins smaller than -5.6; for comparison, the median margin is 0.09 (mean of -1). These large (in absolute value) negative margins have a strong effect on our regression estimates, which is why we exclude them in our baseline analysis.

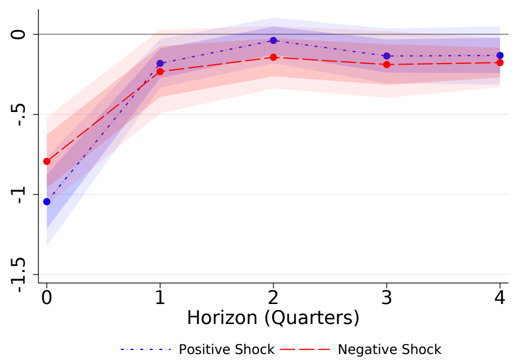
Figure 10, Panel (a), shows the response of margins to the cost innovation, without allowing for differential effects depending on leader and industry concentration. Margins decrease significantly upon impact and remain negative for another quarter. Because our cost innovations are in log terms, the estimated effect at $h = 0$ suggests that margins decrease by about 0.01 in response to a one percent cost innovation. The estimated coefficient on the interaction term Cost-Innovation*HHI in Panel (b) shows that the decline in margins is significantly muted in more concentrated industry. The estimate of close to 8 at $h = 0$ suggests that as industries become more concentrated as witnessed during our sample period ($\Delta HHI = 0.03$), the adverse response of margins to cost innovations is muted by about 25 percent. Panel (c) reveals large and important within-industry heterogeneity as we allow for different responses by industry leaders relative to their followers. The positive point coefficients on the interaction Cost-Innovation*Leader shows that leaders margin decrease significantly less relative to their industry peers. Given the unconditional drop in margins, the point estimate of close to 0.8 indicates that leaders are able to almost entirely insulate their profit margins from cost shocks. To understand the relationship between changes in prices and margin, recall that if all cost were variable—no fixed costs—a complete pass-through of cost into prices would not change profit margins. Thus, our margin results can be consistent with the previously documented higher pass-through in more concentrated industries. Finally, panel (d) shows a negative coefficient on the triple interaction Cost-Innovation*HHI*Leader. Thus, the leader effect is smaller in more concentrated industries.

Our previous results on industry-level cost-shock pass-through depending on concentration revealed significant asymmetric effects depending on the sign of the cost shock. Therefore, in Figure 11, we also analyze asymmetric margin effects depending on the sign of the cost innovation. Panel (a) shows the average relationship across all firms from all sectors, indicating no significant differential effect. Similarly, we do not find a differential response for positive versus negative cost innovations depending on industry concentration (Panel (b)).

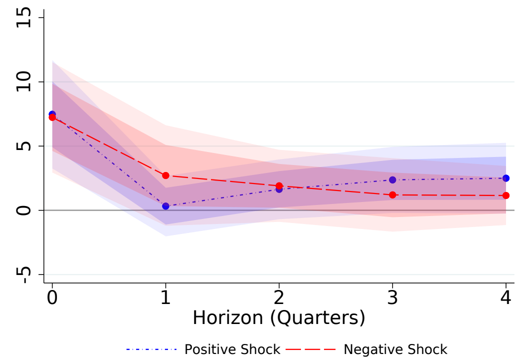
However, in Panel (c), we find statistically significant and economically important asymmetric effects for leaders. In particular, we find that the positive coefficient on the interaction term Cost-Innovation*Leader shown in Table 10, Panel (c), is to a large extent driven by *positive* cost innovations as compared to negative cost innovations.[25] Thus, leaders are able to maintain their level of profit margin in response to positive cost innovations (as compared to followers), but they do increase their profit margins by about the same amount that followers in response to negative cost innovations that bring down their costs. Although we cannot separate the effect of prices and quantity adjustments on firm margins (given data

[25]The differential response to positive versus negative cost innovations is also significant at $h = 0$.

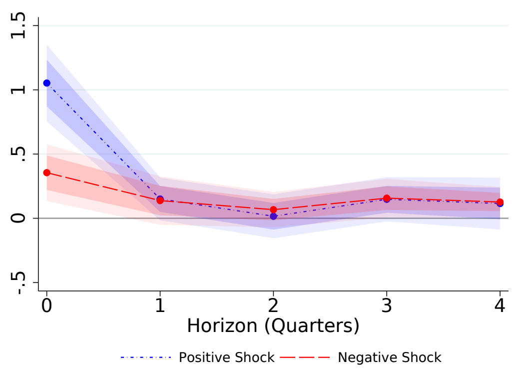
Figure 11: Asymmetric Margin Response to Cost Innovations at the Firm-Level



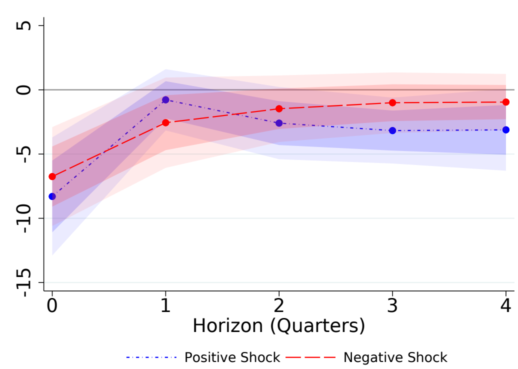
(a) Margin on Cost-Innovation



(b) Margin on Cost-Innovation*HHI



(c) Margin on Cost-Innovation *Leader



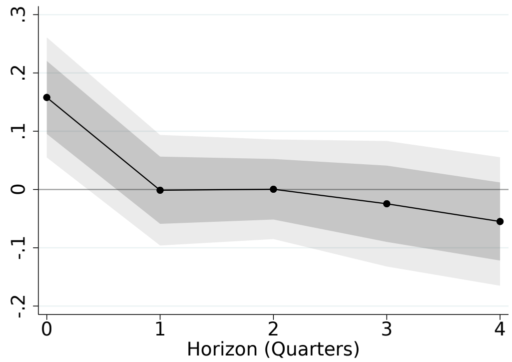
(d) Margin on Cost-Innovation*HHI*Leader

Note: The figure shows estimates from local projections of profit margin, defined as (sales-operating expenses)/sales on the cost shock (Panel (a)), the interaction between cost shock and HHI (Panel (b)), the interaction between cost shock and industry leader indicator (Panel (c)), and the triple interaction between cost shock, HHI and industry leader indicator (Panel d). Blue dotted (red dashed) lines represent the responses to positive (negative) cost shocks. All lower-level interaction terms are included in the specification, but only the relevant estimates are plotted. The data are at the firm-quarter level. All specifications include a set of controls and fixed effects, such that responses are interpreted as within-industry deviations from firm-specific local trend growth. Light shading indicates 90 percent confidence intervals, and dark shading indicates one standard error bands.

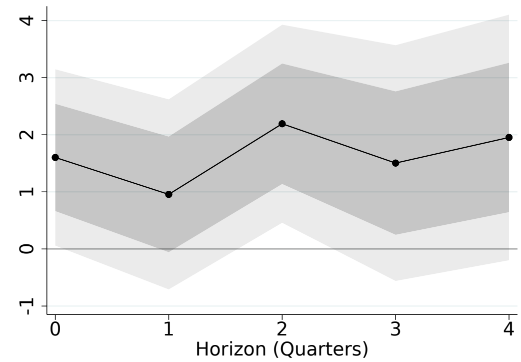
limitations), this key results resembles our earlier finding that positive cost shocks are passed through more to prices and output in concentrated industries while negative cost shocks are not. Panel (d), shows that the differential responses of leaders does not vary additionally on the industry concentration.

We have shown how firms' margins react to a innovation to its cost. How does a firm's margin respond in response to increases in competitors' cost? Evidence on differential responses depending on leader vs followers and depending on concentration can shed further

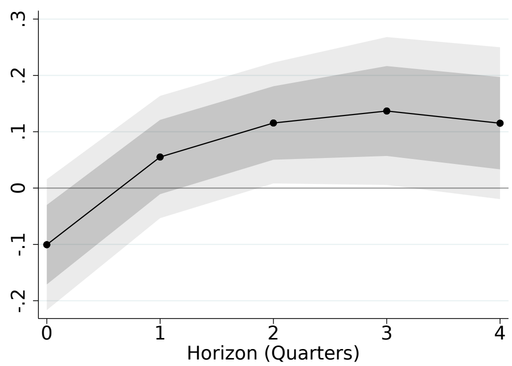
Figure 12: Margin Response to Competitors' Cost Innovations at the Firm-Level



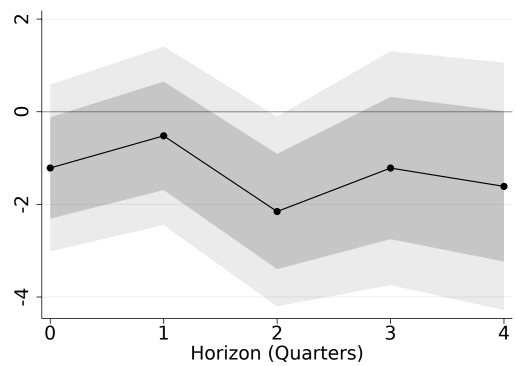
(a) Margin on Cost-Innovations



(b) Margin on Cost-Innovations*HHI



(c) Margin on Cost-Innovations*Leader



(d) Margin on Cost-Innovations*HHI*Leader

Note: The figure shows estimates from local projections of profit margin, defined as (sales-operating expenses)/sales on the (weighted average of) competitors' cost innovations (Panel (a)), the interaction between competitors' cost innovations and HHI (Panel (b)), the interaction between competitors' cost innovations and industry leader indicator (Panel (c)), and the triple interaction between competitors' cost innovations, HHI and industry leader indicator (Panel d). All lower-level interaction terms are included in the specification, but only the relevant estimates are plotted. The data are at the firm-quarter level. All specifications include a set of controls and fixed effects, such that responses are interpreted as within-industry deviations from firm-specific local trend growth. Light shading indicates 90 percent confidence intervals, and dark shading indicates one standard error bands.

light on the differential role of leaders due to market power.[26] Figure 12, Panel (a), shows that after an increase in competitors' cost shock, a firm's margin increases (the effect is marginally significant at 10%). This average effects goes back to about zero one quarter after impact. However, also for the following periods, the margins of leaders are positive relative to industry growth (Panel (c)) Similarly, in Panel (b), we find that the margin increase in response to competitors' shocks is stronger in more concentrated industries. Though stan-

[26]We look at the effect on margins, which depend on both prices and quantities. Due to the usual lack of data availability on broad firm-level prices and quantities, we follow the literature and measure margin.

dard errors are wide, the effect is significant at t =2.) We do not find any evidence that the leader effect interacts with concentration (Panel d).[27]

Our findings about the leaders' margin response to cost innovations are consistent with a large literature on pass-through, mostly in the context of exchange rate pass-through. This literature studies the pass-through at the firm level and documents a highly nonlinear relationship between a firm's market share and pass through. Feenstra et al. (1996) and Garetto (2016) find that the pass through is largest when market shares are very large, as firms face little competition. Pass-through may increase at growing rates from low to high market shares, or decline for small market shares before increasing as market shares are higher. Since we do not observe firm-level prices, we run a similar analysis with margins in Figure B.12. After a cost shock, margins are smaller (but not significantly) for the second size quartile when compared with the first. However, firms in the largest quartile show a significantly larger margins after a cost shock. This U-shaped function of size is maintained over 4 quarters after the shock, albeit with much smaller differences. Under the assumption that our cost measures captures mostly variable costs, margins that are increasing in firm size imply larger pass-through of costs for larger firms.

6 Conclusion

Industry concentration has increased significantly in the United States in the past 20 years, and this trend is projected to accelerate since the onset of the COVID-19 pandemic. We construct a measure of industry cost shocks from firm-level shocks and find that an increase in industry concentration is associated with a significant increase in the pass-through of costs into prices. The differential pass-through to prices depending on industry concentration is particularly stronger for positive cost shocks.

Our findings shed light on the post-COVID inflationary pressures and the linkages between inflation dynamics and rising market concentration. Our result that positive cost shocks are more strongly passed-through in a more concentrated economy suggests that the recent rise in concentration is an amplifying factor for the pass-through of current cost increases emanating from supply shortages, energy price shocks, and labor market tightness. Our results speak to cost-pass through (supply) and not to price and margins adjustments following aggregate demand shocks. Given that in 2020 and 2021 the United States experienced unprecedented aggregate positive cost-shocks across all industries, our results can also reconcile the fact that concentration and market power has been increasing for the past

[27] We also checked for asymmetric effects of competitors' cost innovations on margins, but standard errors are too large to make reliable inference.

two decades at the same time that the United States experienced low inflation, and that concentration and market power can be an important driver of higher inflation now.

More broadly, our results also contribute to our understanding of how concentration and market power are relevant for macroeconomic outcomes, and how aggregate cost pass-through depends on the underlying market structure. Our empirical analysis can be used as a building block in the burgeoning literature that studies these topics—such as the effect of concentration and market power in the transmission of monetary policy (e.g., Wang and Werning, 2020; Mongey, 2021; Baqaee et al., 2021). Although an empirical estimate of how monetary shocks transmission depends on and affects the underlying market structure is outside of the scope of our paper, our estimates can be used to discipline the industry-level response in these models.

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A Examples of Firm-Level Cost Innovations

Freeport-McMoRan Oil & Gas Inc. Freeport-McMoRan is a leading international mining company opertating large, geographically diverse assets with significant reserves of copper, gold and molybdenum. Our cost innovation measure in 2008:Q4 for this firm is 2.37, indicating an increase in more than 230 percent relative to industry and firm trends. Going to the public reports, we verify that, in 2008:Q4, Freeport-McMoRan was experiencing an increase in operating expenses of \$3.8 billion compared to expenses of \$190 million in 2008:Q3, driven by large asset impairments related to the decline in commodity prices amid the weakening of global demand. However, we identify the differential exposure to the commodity price collapse using within-industry comparison. Thus the large increase in expenses is a result of differential inventories and asset holdings (including mill and leach stockpiles). Operating expenses, were down again to \$157 billion in 2009:Q1.[28]

Infineon Technologies AG Infineon is a global semi-conductor manufacturer headquartered in Germany, also listed in the US. Our cost innovation measure in 2009:Q2 for this firm is -1.85. Going to the public reports, we verify that, in 2009:Q2, Infineon was experiencing an decrease in operating expenses of \$685 million. Although this decrease in costs was accompanied by a decline in sales of about \$500 million due to the global economic downturn, the report clearly states that the firm implemented the "most effective cost reduction program Infineon has ever had". According to the reports the implementation of the cost staving plan led to an "annualized savings of about Euro 240 million in operating expenses alone". Thus the large decrease in expenses is, in part, a result of more efficient production process.

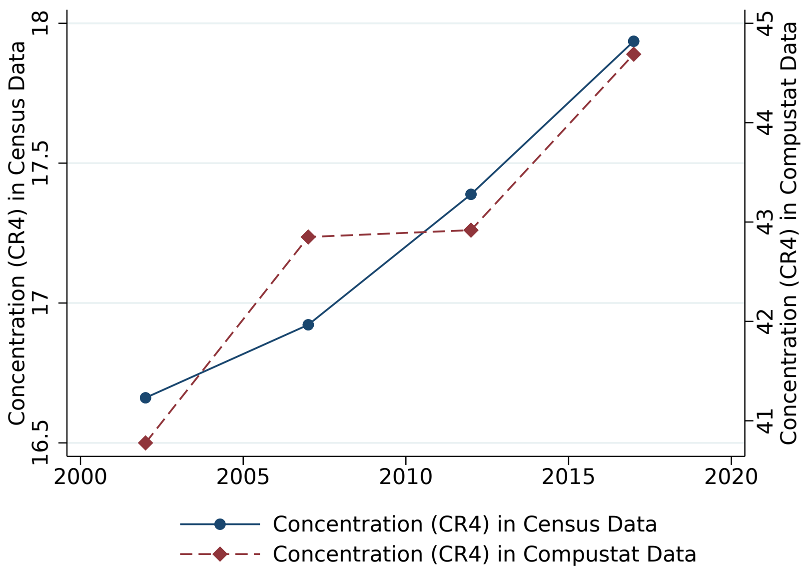
Centrus Enery Corp. Centrus is a global energy company and a leading player in the chemical manufacturing field as a major supplier of low enriched uranium for commercial nuclear power plants. In 2012:Q4, we estimate a cost innovation measure of 1.37 for Centrus, translating to a 137% increase in costs relative to industry and firm trends. During the quarter, Centrus observed a small decline in net revenue of \$160 million coupled with an abrupt increase in operating expenses of \$930 million. Part of the cost increase was driven by the transition away from commercial uranium enrichment and corresponding downsizing of their Paducah Gaseous Diffusion Plant. Though this event was initiated prior to the quarter in question, 2012:Q4 represented a time when a significant portion of the project were expensed. In 2012 alone, Centrus "expensed \$1.1 billion of previously capitalized costs related to the American Centrifuge project." Additionally, the continuing downsizing at

[28]As demand was declining industry-wide in late 2008, Freeport-McMoRan also saw a decline in sales by about \$350 billion in Q4 compared with Q3.

the Paducah Gaseous Diffusion Plant resulted in accelerated expenses, severance pay, and depreciation within the quarter.

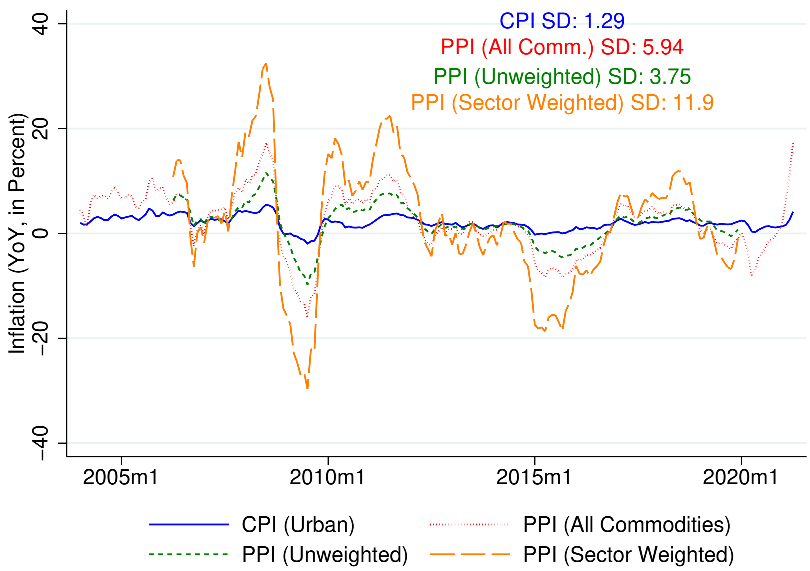
B Additional Figures

Figure B.1: Comparison of Concentration Ratios - Census vs Compustat



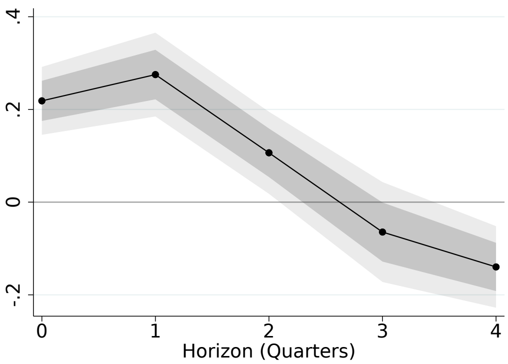
Note: The figure shows the aggregate share (percentages) of sales by industry leaders (top 4 firms in each industry). The raw data are at the NAICS3 level and are aggregated using industry-sales-shares as weights. Data are presented for the different Census waves during our sample period.

Figure B.2: Comparison of CPI and PPI Inflation

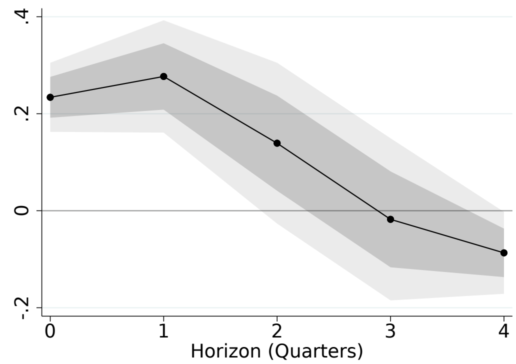


Note: The figure shows different inflation measures (YoY, in percentages) during our main sample period. Standard deviations of the different inflation measures are reported in the figure. PPI (Sector Weighted) is the sales-weighted average NAICS-3-level PPI inflation. Sales weights are computed based on Compustat sales. Source: BEA/BLS, authors' calculations.

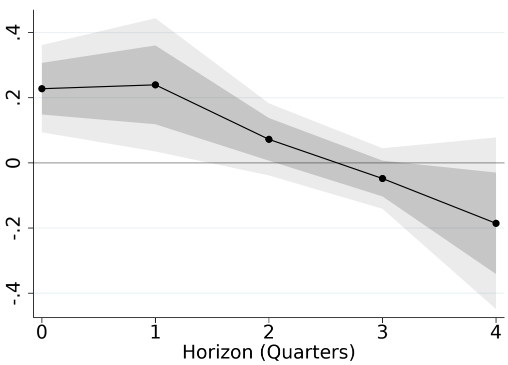
Figure B.3: Level Effect of Price Response with Different Cost Shock Measures



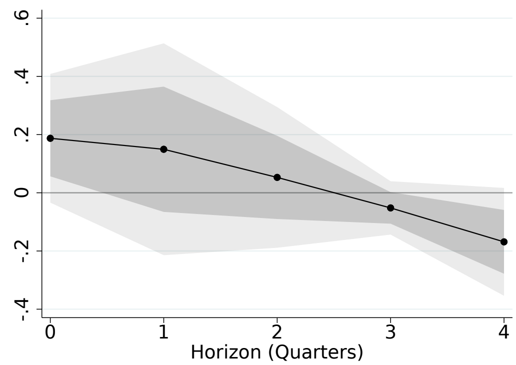
(a) Price on GIV (GIV 1 All)



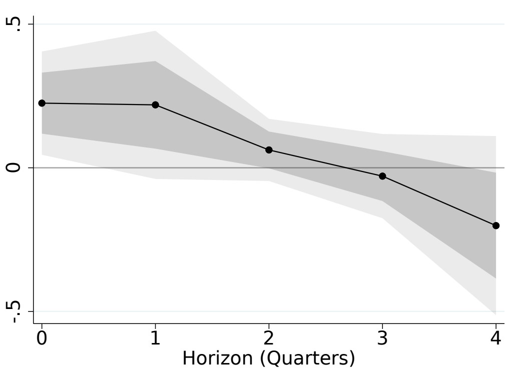
(b) Price on GIV (GIV 1 Top 5)



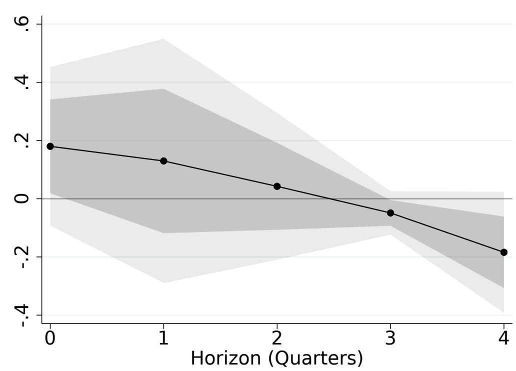
(c) Price on GIV (GIV 5 All)



(d) Price on GIV (GIV 5 Top 5)



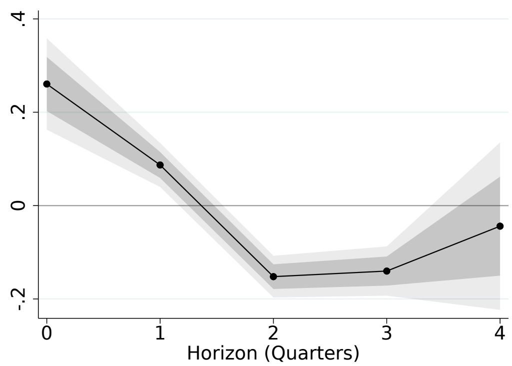
(e) Price on GIV (GIV 6 All)



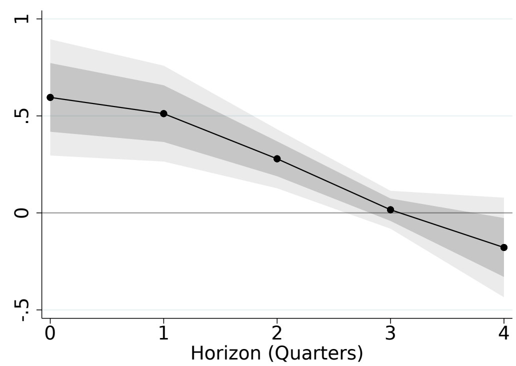
(f) Price on GIV (GIV 6 Top 5)

Note: Robustness analysis to our main results in Figure 2, Panel (a), using different versions of cost shocks (GIVs). Top 5 means that only the cost innovations of the largest 5 firms within each industry are aggregated, see Gabaix and Koijen (2021).

Figure B.4: Main Results in Log Differences



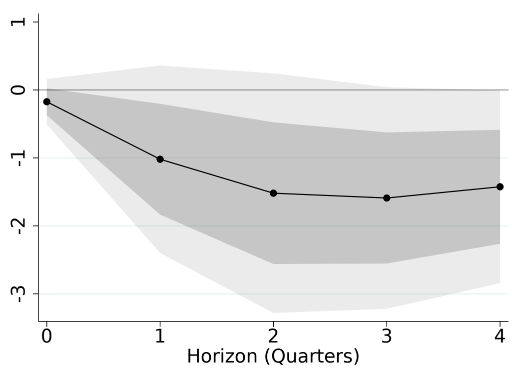
(a) Price Growth on GIV



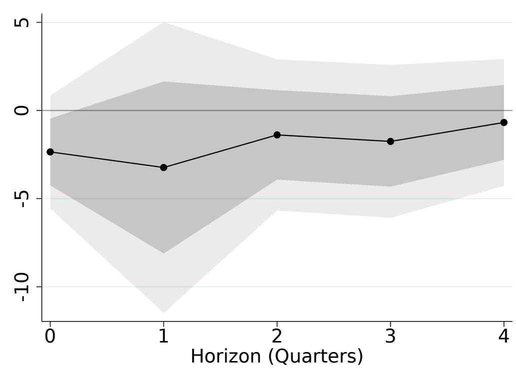
(b) Price Growth (YoY) on GIV

Note: Robustness analysis to our main results in Figure 2, Panel (a). Here we use log differences and log year-over-year differences of cost and prices instead of log levels as in the main part.

Figure B.5: Additional Results on the Role of Concentration: Effect of Endogenous Costs and Response of Costs



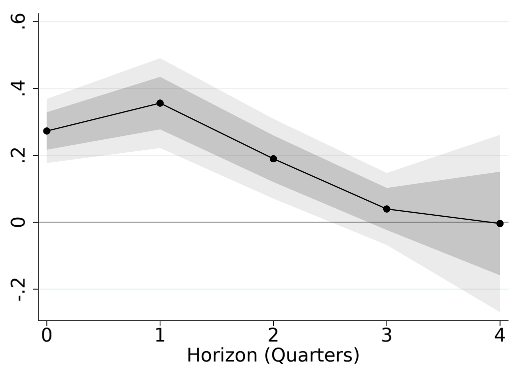
(a) Prices on Cost*HHI



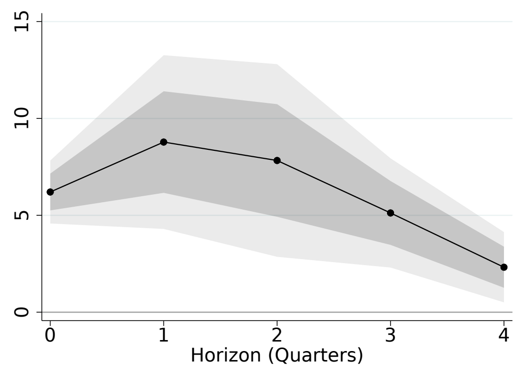
(b) Cost on GIV*HHI

Note: Additional Results supporting our main finding on concentration shown in Figure 6. Panel (a)) shows attenuated results when using an endogenous cost measure instead of the GIV. Panel (b)) shows the endogenous response of costs depending on concentration.

Figure B.6: Only industries with 20 or more firms: $N > 20$



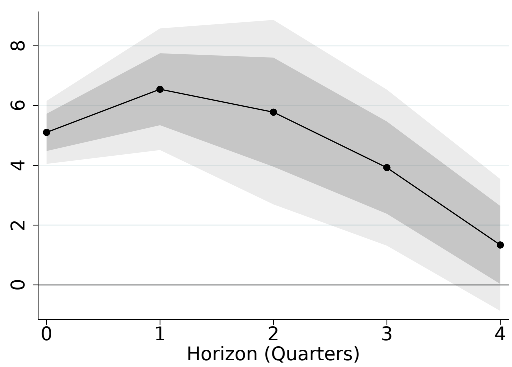
(a) Price on GIV



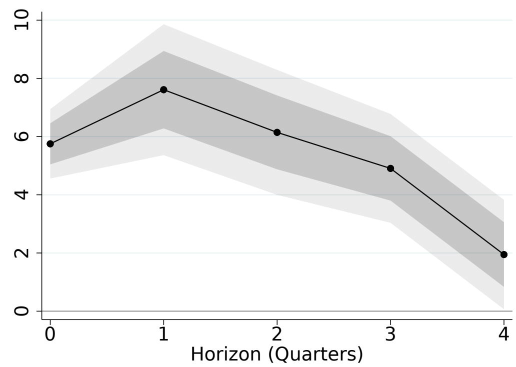
(b) Price on GIV*HHI

Note: Robustness analysis to our main results in Figure 2, Panel (a), and Figure 6, Panel (a).

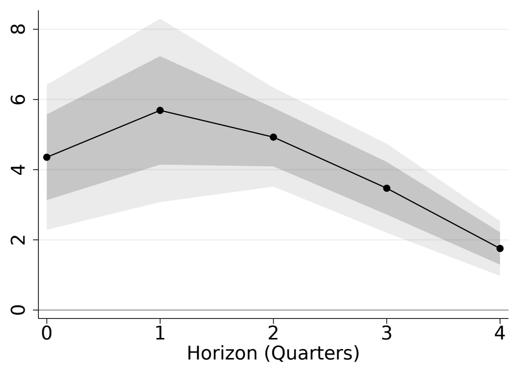
Figure B.7: Concentration Effect of Price Response with Different Cost Shock Measures



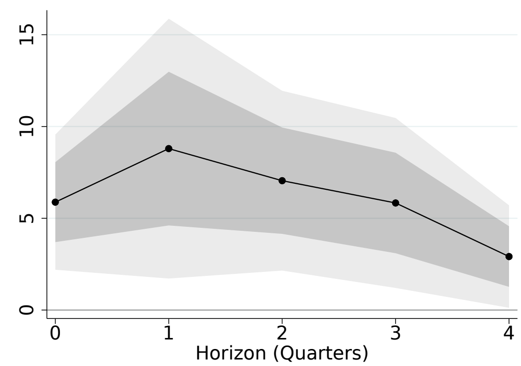
(a) Price on GIV (GIV 1 All)



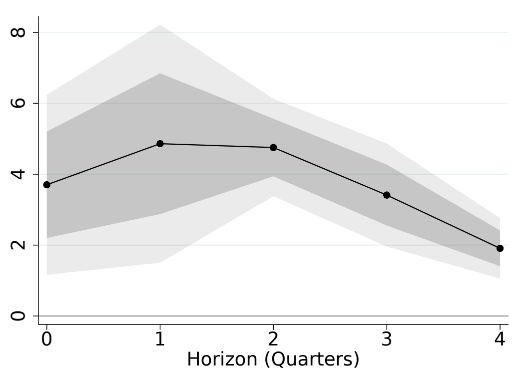
(b) Price on GIV (GIV 1 Top 5)



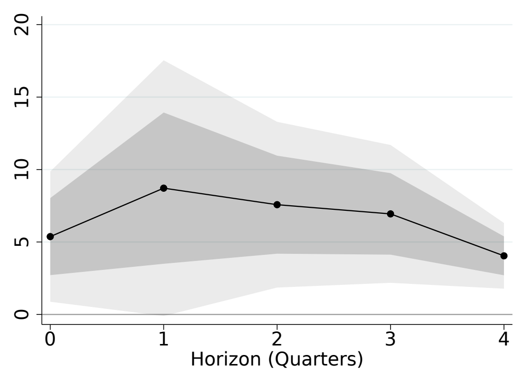
(c) Price on GIV (GIV 5 All)



(d) Price on GIV (GIV 5 Top 5)



(e) Price on GIV (GIV 6 All)



(f) Price on GIV (GIV 6 Top 5)

Note: Robustness analysis to our main results on the concentration differential in Figure 6, Panel (a), using different versions of cost shocks (GIVs). Top 5 means that only the cost innovations of the largest 5 firms within each industry are aggregated, see Gabaix and Koijen (2021)

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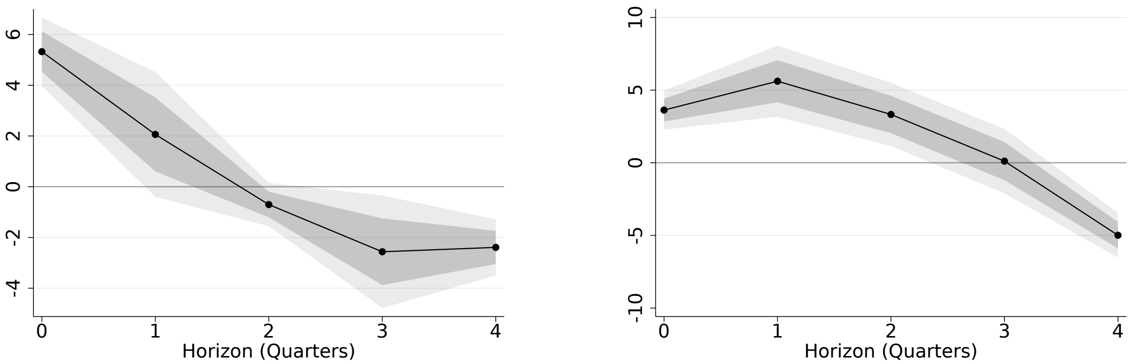
Figure B.8: Concentration Results in Log Year-Over-Year Differences

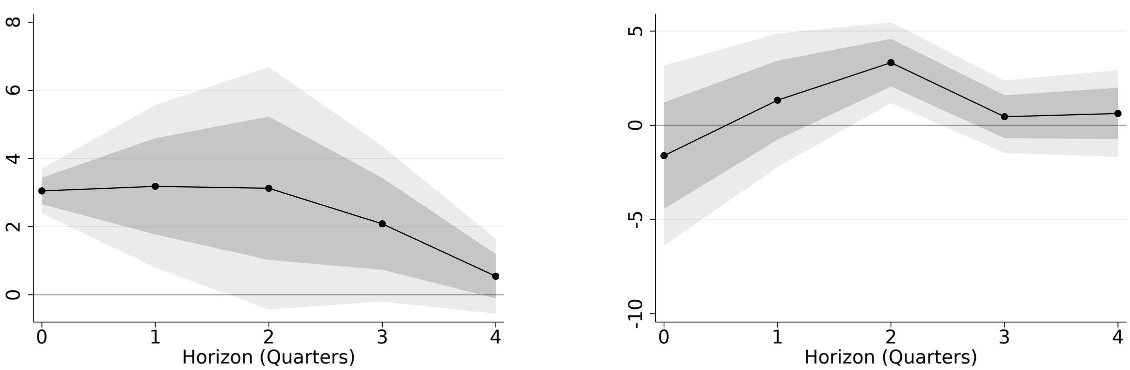


(a) Price Growth on GIV*HHI

(b) Price Growth (YoY) on GIV*HHI

Note: Robustness analysis to our main results in Figure 6, Panel (a). Here we use log differences and log year-over-year differences of cost and prices instead of log levels as in the main part.

Figure B.9: Results on Concentration with Different Cost Measure: CoGS vs Non-CoGS

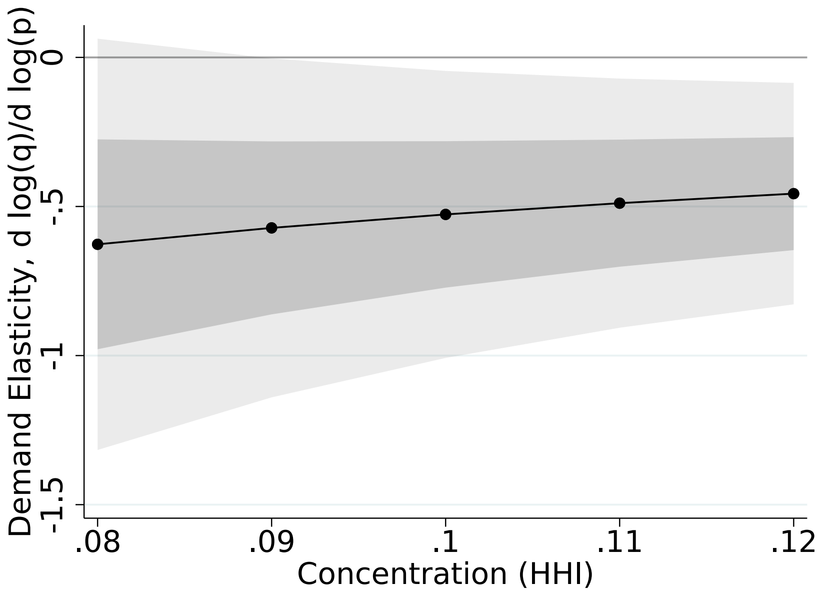


(a) Price on GIV*HHI

(b) Price on GIV*HHI

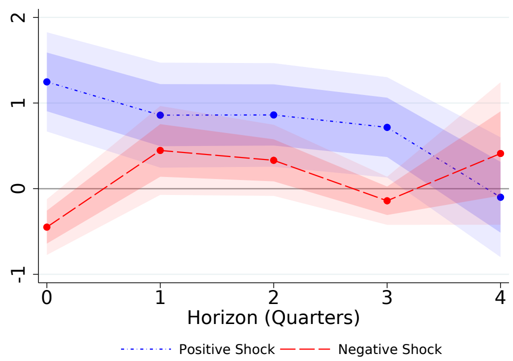
Note: Robustness analysis to our main results in Figure 6, Panel (a), using a proxy for variable costs (CoGS) and fixed costs (non-CoGS).

Figure B.10: Demand Elasticity and Industry Concentration

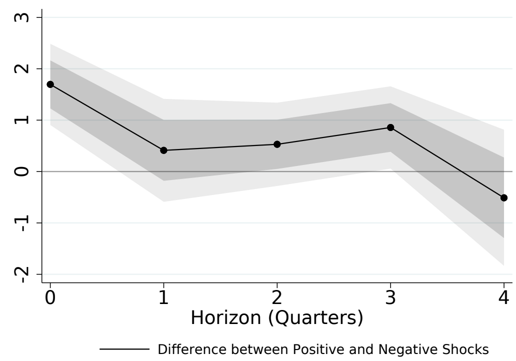


Note: Demand elasticity depending on HHI estimated from output and price responses at $h = 2$.

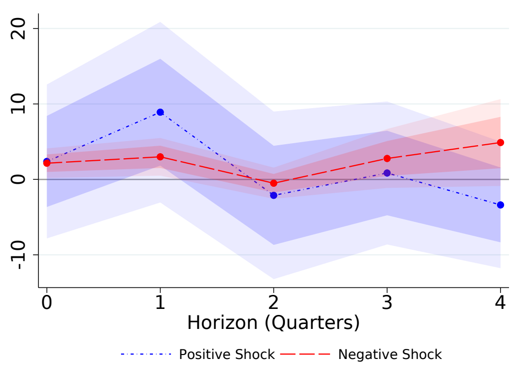
Figure B.11: Asymmetric Cost Responses



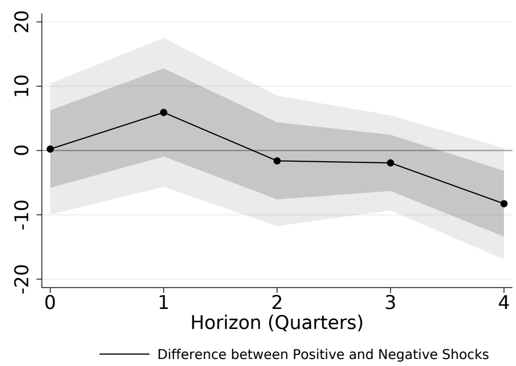
(a) Cost on GIV Level



(b) Cost on GIV Level (diff)



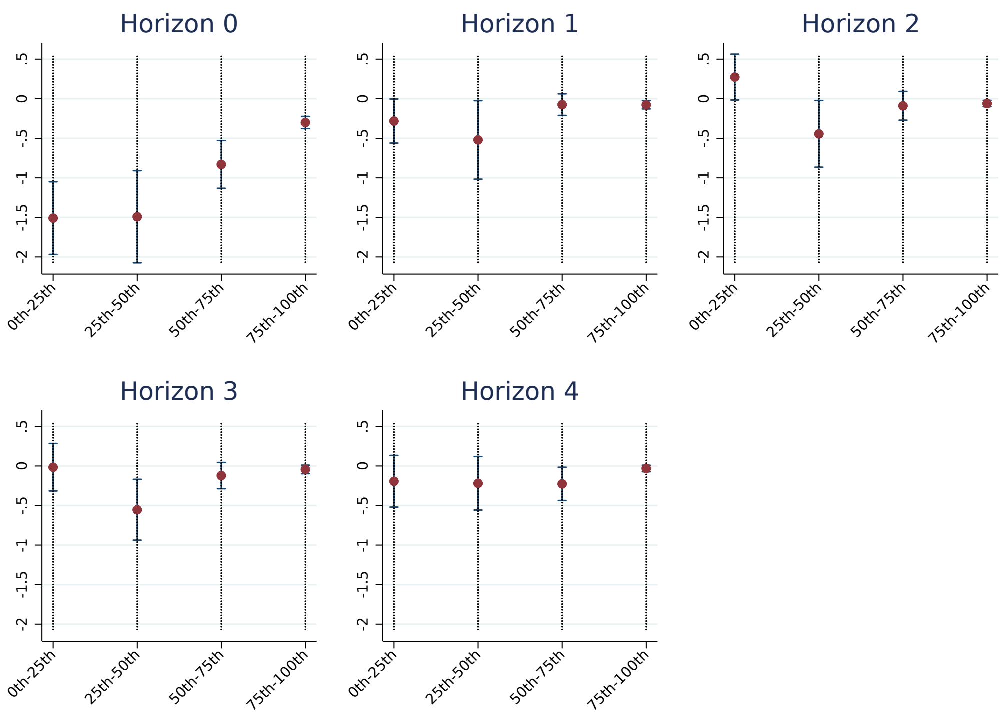
(c) Cost on GIV*HHI



(d) Cost on GIV*HHI (diff)

Note: The figure shows estimates from local projections of Log Operating Expenses on the cost shock (Panel (a)) and the interaction between cost shock and HHI (Panel (c)). Responses are split depending on the sign of the cost shock: Blue (red) lines represent the responses to a positive (negative) cost shock. The differences between the blue and red lines are shown in Panels (c) and (d). All specifications include a set of controls and fixed effects, such that responses are interpreted as deviations from local trend growth. Light shading indicates 90 percent confidence intervals, and dark shading indicates one standard error bands.

Figure B.12: The Effect of Cost Innovations on Margin by Firm Size (Quantile) Groups



Note: Quantiles calculated using sales within NAICS-3-quarter. Observations are dropped for NAICS-3-quarter-quantiles that have fewer than five firms.

C Additional Tables

Table C.1: Summary Statistics of Different Cost Shocks

	mean	sd	min	p5	p25	p50	p75	p95	max
GIV (Model 1)	0.005	0.070	-0.708	-0.097	-0.021	0.004	0.035	0.100	0.459
GIV (Model 2)	0.004	0.072	-0.517	-0.101	-0.025	0.003	0.037	0.104	0.399
GIV (Model 3)	0.003	0.064	-0.668	-0.088	-0.023	0.000	0.030	0.093	0.425
GIV (Model 4)	0.002	0.048	-0.565	-0.066	-0.017	0.000	0.023	0.071	0.355
GIV (Model 5)	0.002	0.045	-0.503	-0.061	-0.015	0.000	0.019	0.066	0.282
GIV (Model 6)	0.002	0.041	-0.424	-0.053	-0.014	0.000	0.017	0.061	0.285
Observations	3544								

Note: Summary statistics of industry-level cost shocks.

Table C.2: Correlation of Different Cost Shocks

	(1)					
	GIV (Model 1)	GIV (Model 2)	GIV (Model 3)	GIV (Model 4)	GIV (Model 5)	GIV (Model 6)
GIV (Model 1)	1					
GIV (Model 2)	0.473	1				
GIV (Model 3)	0.877	0.483	1			
GIV (Model 4)	0.737	0.463	0.830	1		
GIV (Model 5)	0.683	0.413	0.771	0.884	1	
GIV (Model 6)	0.654	0.404	0.732	0.842	0.955	1

Note: Pairwise correlations of industry-level cost shocks.